Corporate Dark Money in Politics: Evidence from India

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January 15, 2026

This paper empirically investigates the use and rationale of corporate dark money in politics using a unique regulatory timeline in India. From 2018 onwards, firms were allowed to make unlimited undisclosed donations to political parties via "electoral bonds." A 2024 Supreme Court ruling banned the practice and retroactively made public the details of all $2 billion of such donations. We link this unique data to a newly assembled dataset of publicly disclosed contributions going back to 2003 to examine how donors, recipients and patterns of corporate donations change when an opaque channel for campaign financing is introduced. We present four novel facts. First, once allowed, undisclosed donations immediately dwarf in aggregate amount disclosed donations. Second, firms that are larger and more exposed to political parties and investors disproportionately select into the opaque channel. Third, firms that donate without disclosure requirement do so more often, in larger amounts, and to a wider range of political parties than both disclosed donors and their own behavior before the opaque channel became available. Fourth, losing confidentiality is costly to donors: when donation data becomes public, donors' market capitalization experience negative abnormal returns that are significantly larger than the donations, suggesting high private returns to confidential donations. This study uncovers the significant demand from firms for making hidden political donations, and provides supportive evidence for opacity lowering the reputation and retaliation costs of corporate financing of political campaigns, thereby fueling the quantity and changing the source and destination of corporate donations in the search for potential quid pro quos.

*London Business School, sukritp@london.edu. †INSEAD, boris.vallee@insead.edu. This work benefited from helpful feedback from Pat Akey, Abhit Bhandari, Emanuele Colonnelli, Devesh Kapur, Ararat Gocmen, Danny Hidalgo, Evan Lieberman, Max Miller, Benjamin Munoz, Vishan Nigam, Tomoya Sasaki, David Szakonyi, Ben Ross Schneider, Antoinette Schoar, Aliz Toth, Tim Werner, Luigi Zingales, participants at the 2025 CEPR Political Economy, T-PEC 2025, NPEC 2025, SBE 2025, CBS-Princeton Money in Politics 2025, HBS Finance Workshop.

1. Introduction

Political donations, as well as their rationale and effects, have been extensively studied. Virtually every work from this literature relies on publicly disclosed donations due to obvious data availability considerations. However, publicly disclosed donations are likely just the tip of the iceberg, and may systematically differ from undisclosed ones.[1] For special interest groups like corporations or high net worth individuals, legal "dark" money channels exist in many countries to fund political campaigns outside public view.[2] Understanding the role of dark money in politics is therefore crucial to political economy, and of growing importance given recent legal or technological developments, such as the rise of Super PACs in the US, or the crypto-currency ecosystem. Donation opacity is also of particular interest in developing countries, where illegal (and therefore undisclosed) donations might be more frequent and even legal donations whose disclosure are mandatory may remain hidden because of weak enforcement of disclosure rules or poor systems of data collection.

Better understanding the role of dark money in politics raises two immediate empirical challenges: a measurement one and a counterfactual one. First, while scholars have taken a forensic approach to uncover hidden corporate-political links—e.g. via philanthropic giving (Bertrand et al. 2020), biographical connections (Bertrand et al. 2018), local commodity price distortions around elections (Sukhtankar 2012), and even sudden deaths of known donors (Battaglini et al. 2024)—these approaches paint at best a partial and noisy picture of the place of dark money in politics. Second, without a sharp introduction of an opaque channel and comprehensive data on disclosed donations before and after this introduction, it is difficult to study how the existence of a dark money channel affects overall donation activity.

This paper aims to address these central challenges by leveraging a unique regulatory timeline in India—the world's largest democracy, where elections are among the most expensive in the world, and corporate funding is particularly salient (Kapur and Vaishnav 2018). From 2003 onwards, corporations in India could only make publicly disclosed political donations, which would be disclosed by political parties in annual contribution reports. In 2017, the government introduced a new channel for companies to donate to political parties confidentially by purchasing "electoral bonds."[3] In this scheme, donors could purchase these electoral bonds in fixed denominations and deposit them in political parties' accounts located in specific branches of a nationalized bank (the State Bank of India). These donations were completely unobservable by the public, the media or non-recipient political parties, and unlimited in their amount. In February 2024 however, a Supreme Court ruling forced the government to reverse its policy and

[1] See for instance, Wood (2018); Bombardini and Trebbi (2020); Denes et al. (2022); Bombardini and Trebbi (2025). Battaglini et al. (2024) suggests this might be an explanation for the puzzle about why there is so *little* money in politics despite the large economic stakes (Ansolabehere et al. 2003).

[2] Sometimes called "dark" or "hidden" or "soft" (Apollonio and Raja 2004) , or "grey" (Grumbach and Pierson 2019), or "veiled" (Garrett and Smith 2005), these are all terms for hard to size and trace political giving.

[3] Despite their name, electoral bonds are not bonds but vouchers that may be deposited in party bank accounts.

retroactively reveal granular details of all previously-hidden political contributions. By compiling these data and linking them to a newly assembled dataset of publicly disclosed contributions going back to 2003 as well as administrative data on Indian corporations, we aim to shed light on the nature and scope of corporate dark money in the financing of political campaigns.

More specifically, this study tackles the following research questions: How does opacity affect corporate firms' political donations? How does it differ from *disclosed* giving? Who values confidentiality when making political donations and why? What is the value of such confidentiality?

We first provide four novel empirical facts that speak to these questions. First, once an opaque donation channel is open for corporations, undisclosed donations far outpaces disclosed ones, and the total amount of donation rises significantly. While political parties raised around \$1.2 billion in disclosed corporate donations over 20 years from 2003-2023 in aggregate, they raised almost \$2 billion via electoral bonds sales in the 6 years following their introduction. Across both channels, the corporate share of donations far dominates individual donations—which differs from patterns noted in the US where the marginal donor is an individual (Ansolabehere et al. 2003), and instead aligns with other developing countries, like Brazil, where corporations tend to be responsible for most political financing (Samuels 2001).[4]

Second, the characteristics of firms that participate in each channel differ, with only a small share of firms participating in both channels. While over 7,600 distinct firms made disclosed donations to political parties since 2003, and around 1,100 bought electoral bonds, only approximately 150 companies participated in both channels over the 2018-2024 period. We compare firm-level characteristics by linking both sets of firms to the Ministry of Corporate Affairs' registrar of all (approximately 2 million) formally registered businesses in India as of 2020. Undisclosed donors tend to be significantly larger (as measured by their share capital, a.k.a paid up capital in India), older, and more likely to be publicly listed when compared to disclosed donors, and even more so when compared to the whole firm population. The average undisclosed donor therefore has a book equity value that is more than four times larger than the one of the averaged disclosed donor. Political factors also affect firms' use of the opaque channel. Local exposure to multiple competing political parties and closely fought elections predicts firm participation as electoral bond buyers.

Third, when firms give to political parties without public disclosure, they donate more often, in greater amounts, and to a broader set of parties compared to the ones that do so publicly. Opaque donors are more persistent donors also—if a firm donates in year t, the odds it donates again in year $t + 1$ is 2.5 times as high for electoral bonds compared to disclosed donors (10% vs. 25%). As noted in Puri (2024), disclosed donors tend to make small and sporadic donations to a single political party, which more closely resembles individual rather than corporate donor behavior in the American context. Opaque donors therefore behave more similarly to scholarly

[4]As long as corporate donations were permitted (Balan et al. 2025).

expectation of corporate political donors.

We document these differences in both the cross-section and the time-series: previously disclosed donors change their donation patterns once they can do so without disclosure. This latter fact suggests that selection is unlikely to fully explain the cross-sectional difference.

These three sets of facts suggest that the existence of an opaque channel meaningfully affects the nature of campaign finance, inviting a different set of actors to participate, and producing distinct patterns of political giving.

Fourth, we document that making undisclosed donations public has significant value implications for the donor firms. When conducting a stock price event-study for publicly listed firms at the time of the release of the electoral bond data, we find significant negative abnormal returns for firms that are revealed as undisclosed donors to political parties. The economic magnitude of the market reaction suggests high private returns to undisclosed donations.[5]

Altogether, these empirical facts are consistent with corporations making undisclosed political donations in the search for quid pro quo, while minimizing the reputation and retaliation costs that can be associated with such actions. Noticeably, introducing an opaque donation channel may foster political pluralism as donors are more likely to donate to opposition parties when their donations are undisclosed. However, the significant increase in aggregate donations associated with such a channel raises concerns that it allows corporations to gain disproportional political influence. An open question is to which extent undisclosed political donations crowd out illegal ones, as it was the initial motive presented for the electoral reform.

This paper contributes to the growing literature on dark money in politics. While anecdotal and journalistic accounts of undisclosed campaign finance abound (Mayer 2016), academic treatment has remained more limited, making the normative case for transparency (Wood 2018; Bebchuk et al. 2020), or studying strategic disclosure theoretically (Schnakenberg and Turner 2025; Jia et al. 2023). Recent work attempts to estimate the extent of disclosed contributions by tracing more obscure channels of spending (Denes et al. 2022; Bombardini and Trebbi 2025), but in general empirical visibility into firm-level participation in dark money channels remains rare. We exploit a unique disclosure event in India to provide the first comprehensive account of anonymous corporate giving in a major non-U.S. democracy, offering new insight into the scale, rationale, and participants in dark money systems.

Bringing novel administrative data, this paper makes a further empirical contribution in two ways: covering an emerging economy, and studying a broad set of corporations. Alongside Puri (2024) for India, Boas et al. (2014); Avis et al. (2022) for Brazil and (Gulzar et al. 2022) for Colombia, this paper is one of the first systematic studies of campaign finance in a non OECD country. Existing research on corporate-political links in India has so far been more conceptual in nature (Kohli 2012; Jaffrelot et al. 2019), and empirical studies tend to take a more investigative approach—examining commodity prices around election times (Sukhtankar 2012; Kapur and

[5] While the ex post negative value effects do not necessarily imply ex ante gains, we are currently working on providing a more comprehensive pictures of the firm value implications of the opaque donation channel.

Vaishnav 2013) or combing through newspaper reports for corporate-political co-presence (Chen et al. 2025). Second, by using comprehensive administrative data on all firms in the formal sector, this paper moves beyond inherent limitations in the literature on corporate politics that only studies large publicly held companies due to data availability.

Finally, this study builds on a rich literature examining the value of political connections for firms through stock price event studies conducted around a political shock. These political shocks include the death of a patron (Fisman 2001), political appointments (Acemoglu et al. 2016), election turnover (Wagner et al. 2018), and coups (Dube et al. 2011). This study is most similar to Werner (2017) and Minefee et al. (2021) who exploit accidental disclosures of corporate donors to Republican-associated nonprofits, and parallels work in finance on surprise corruption disclosures and firm performance (Colonnelli and Prem 2022; Colonnelli et al. 2022).

In finding a sharp negative market response to learning about a company's political activity, this work contributes to a small but burgeoning literature that identifies potential *costs* of political connections to firms. Bertrand et al. (2018) and Akcigit et al. (2023) describe how political connections may distort firms operations either through political pressure around election time, or by creating conditions that promote under-investment in innovation. Studies increasingly show how negative attitudes and perceptions around revealed corporate political activity takes a toll on firm performance Borisov et al. (2016); Katic and Hillman (2023). For instance, one line of studies show how a company's sales may suffer once consumers learn about and disagree with its political leanings (Panagopoulos et al. 2020; Bhandari 2022; Conway and Boxell 2024) In a conjoint experiment setting, Kubinec et al. (2021) finds companies' potential political connections to dissuade hypothetical investors. This paper studies this mechanism outside an experimental setting, with real market reactions rather than reported preferences, and with an ability to measure how long these effects last.

The remainder of the paper is structured as follows. Section II provides some background and describes the data. Section III establishes a set of empirical facts. Section IV provides some discussion on the mechanism underlying the use of undisclosed donations by corporations and associated implications, and Section V concludes.

2. Corporate Political Donations in India: Background and Data

2.1. Institutional background and regulatory timeline

This section provides a short overview of campaign financing and its recent evolution in India.[6]

India is a federalized parliamentary democracy with competition between multiple political parties at both the national and state levels. Despite operating single member districts with first-past-the-post electoral (FPTP) systems, where citizens vote for members of parliament and

[6]This is a summary that draws on more detailed accounts available in Sridharan (1999); Gowda and Sridharan (2012); Kapur and Vaishnav (2018); Jaffrelot et al. (2019).

members of state assemblies directly, political parties tend to hold primacy over individual politicians. This situation is comparable to the US and in contrast to other settings, like Brazil, where candidates dominate party affiliation, and partly as a result of a 1980s anti-defection law where party members are barred from voting against the party whip (?). As a result, political financing is enshrined legally at the party level. India has a long history of corporate financing of politics. Even before independence, industrialists such as G.D. Birla were key funders of the Indian National Congress. In the early post-independence years, the dominant Congress Party exchanged regulatory permissions and licenses for financial support from business houses (Kochanek 1974). While such corporate donations were legal under the 1956 Companies Act, Prime Minister Indira Gandhi's 1969 banned corporate contributions (without replacing them with public financing mechanisms). Such legal decision moved corporate donations underground into an era of "briefcase politics" (Kochanek 1987).

India's liberalization in the 1980s and 1990s catalyzed changes in party finance law. In 1985, corporate donations were re-legalized but capped at 5% of the three-year trailing average of net profits, subject to board approval and disclosure in financial statements. This cap was raised to 7.5% in 2012. A key turning point for transparency came in the 2000s, when the 2005 Right to Information (RTI) Act passed, empowering citizens to petition for data. In 2008, the NGO Association for Democratic Reforms (ADR) successfully used the RTI to compel disclosure of all political contributions above INR 20,000, retroactively applicable to 2003. The Election Commission of India (ECI) now publishes these financial disclosures online, and ADR transcribes them into searchable formats. These reforms also incentivized a shift to legality: in 2003, corporate and individual donations became fully tax deductible; and in 2012, the creation of Electoral Trusts allowed corporations to pool and distribute funds transparently under ECI oversight.

On February 1st, 2017, the ruling BJP party announced a number of changes to the campaign finance landscape in 2017 Finance Bill presented to parliament. First, it removed the cap on corporate donations, and dropped the requirement to disclose party contributions in companies' annual reports. Still, political parties were required to disclose any donations above INR 20,000 (ca. USD300). Second, it introduced a new Electoral Bond Scheme as an alternate mechanism for party financing. In this scheme, individuals or companies could purchase bearer bonds of different denominations, and deposit them into the accounts of political parties at the State Bank of India (SBI), on a set of pre-specified days in a year. These donations would retain their tax advantage, but incurred no disclosure requirement. While the government justified this opacity as necessary to curb "black money,"[7] critics argued that it merely legalized secrecy (Vaishnav 2019).[8]

[7]"Black money" was top of the national political agenda at the time. In 2014 the BJP had been voted in on the back of an anti-corruption swing against the INC-run coalition, and in 2016 the BJP waged an attack on "black money" in the economy by demonetizing 86% of currency bills in circulation overnight, with major macroeconomic consequences (Lahiri 2020; Chodorow-Reich et al. 2020).

[8]Legal details about the Electoral Bond Scheme and its timeline are documented in detail on the website of legal watchdog, Supreme Court Observer: https://www.scobserver.in.

Starting January 2018, companies could choose whether to make donations to parties that would be disclosed if above INR 20,000 (a high amount for individuals, but not for formally registered businesses), or whether to make undisclosed deposits of electoral bonds in party bank accounts. After over a year without any tracking, starting in April 2019, the Supreme Court modified the scheme to ensure the State Bank of India would collect the details of these electoral bond purchasers and share them with the ECI, which would then produce annual reports of aggregate fundraising.

After the electoral bond scheme was announced, the civil society organization "Association for Democratic Reform" challenged the legality of the scheme. In October 2023, the Supreme Court heard oral arguments, and on February 15, 2024 –against popular expectations– the Court struck down the scheme as unconstitutional and required the names of all donors to be published on the ECI's website by March 6. After a small delay, on March 12, SBI submitted two lists to the ECI: the list of bond purchases with details of the bond purchaser, and the list of deposits into party accounts.[9] On March 14, the ECI published these two lists on its website. The most glaring omission at this point was the two lists could not be combined: it was impossible to identify *which party* each donor was donating to. Upon pressure from the Supreme Court, the ECI released fresh data on March 21 with donation-specific identifiers that allowed the two lists to be linked, enabling analysts and journalists to trace firm-level political contributions with unprecedented clarity.

2.2. Data

Our data set is built from three main sources: the electoral bond registry released by the Supreme Court, the regular donation registry disclosed by the Electoral Commission of India, and administrative data on Indian corporations. We complement these main sources with a variety of data sources, including financial data from Prowess and Datastream and data on election results.

Undisclosed donations ("Electoral Bonds"). The main data source for this paper is the list of electoral bond purchases published on the ECI website on March 14, 2024. This list contains information about the date of purchase, name of purchaser, and denomination of bond bought, for almost 19,000 purchases, made between April 2019 and February 2024, to 26 parties, amounting to over 120 billion INR (approx. 1.7 billion USD) (Traveli and Kumar 2024).

A key challenge with this data is that electoral bond buyers are not consistently identified. For instance, the original list reports donations from `Achintya Solar Power Private Limited` and `Achintya Solar Power Pvt Ltd`, which are the same legal entity, but would be counted as distinct entities using an exact string matching procedure. Instead, we develop and use a web-scraping based entity resolution algorithm that links each corporate donor to its

[9] On March 4, SBI requested an extension until June 30—after the national elections, slated for April-May 2024. But the SC rejected this request and gave a new deadline of March 15.

unique 21-digit corporate identification number (CIN), which helps resolve cases of ambiguous or duplicated entities.[10]

The CIN is available to all formally registered businesses in India. While there is no size floor to formally incorporate, it does come with onerous regulatory requirements like annual financial reporting to the Ministry of Corporate Affairs, and convening a minimum of a 2-person board of directors, which filters out smaller "mom and pop" *kirana* stores and micro enterprises which may remain informal or register for a less onerous tax ID (GSTIN) rather than full incorporation. Out of the over-1100 unique electoral bond buyers, approximately 800 are corporate donors with corporate ID numbers, making almost 97% of donation value.

Disclosed donations. We complement the electoral bonds data with disclosed donations from parties' annual disclosure to the Election Commission of India, as recently collected and standardized in Puri (2025) and Puri (2024). In short, we scrape the database of political donations manually transcribed by the NGO ADR and published to its website `myneta.info`. We identify corporate donors bysearching for various corporate-related strings (like "private limited", etc.), and match irregularly recorded corporate donors to their consistent CIN number via the same entity-resolution algorithm described earlier. For missing CINs, we augment this automated procedure with an extensive manual process of collecting unique tax IDs (PAN numbers) recorded in the parties' annual contribution reports, and matching these tax IDs to CIN. For donations by electoral trusts to political parties, we hand collrvy all contributions made to electoral trusts each year, and fetch the corporate ID numbers.

Overall, we recover over 7,600 unique corporate entities making approximately $1.2 billion dollars in donations to 42 political parties between 2003 and 2023.

Adminstrative firm-level data. We obtain information on firm characteristics using the CIN number and associated corporate registrars from the Ministry of Corporate Affairs (MCA). The Corporate ID Number, which is the official unique identifier for firms in India, contains in itself useful firm-level characteristics. The 21-digit CIN itself encodes several useful pieces of information:

For instance, `Nalli Silk Sarees Pvt Ltd`, a purveyor of women's garments in India, has the following CIN number:

`U52100TN1993PTC025196`

This string embeds the following information:

- `U`: Listing status (company)
- `521000`: National industry code[11] (retail trade)

[10] See Puri (2025) for details about this entity resolution algorithm, and its performance compared to standard fuzzy and probabilistic string matching techniques.

[11] Which is harmonized with the International Standard Industrial Classification (ISIC).

- `TN`: State of registration (Tamil Nadu)
- `1993`: Year of registration (1993)
- `PTC`: Company type (private limited company)
- `025196`: Company's registration number

In addition, the Ministry of Corporate Affairs (MCA) publishes the full registrar of all companies registered in India going back to 1857 on its website, with firms identified by their corporate ID number. Even though parts of a firm's CIN number may evolve as its corporate structure evolves (e.g. goes from privately held to publicly listed) or the state of registration modifies with the creation of a new state (e.g. the 2013 split between Telangana and Andhra Pradesh), the six digit registration number remains consistent and tied to a single corporate entity.

We collect this complete registrar of almost 2 million firms that comprise the formal sector of India, which helps provide a baseline to compare donors with non-donor firms. In addition, this registrar provides a measure of each firm's size by reporting its paid up capital (equivalent to a company's share capital).

For a subset of companies in our data and all publicly listed companies across both the Bombay and National Stock Exchanges, we collect a richer set of financial variables recorded annually and made available via Prowess through CMIE—which collects data on over 50,000 of the largest companies in India and is commonly used in academic studies relating to Indian firms.[12] For daily stock price data, we use Datastream.

3. Basic Facts

In this section, we leverage our unique dataset resulting from the Indian regulatory timeline to uncover a set of novel stylized facts about dark money in politics.

3.1. Aggregate donation volume increases sharply, driven by confidential donations

The introduction of an opaque channel for corporate donations is associated with a sharp increase in the total volume of corporate donations going to political parties. See figure A1. Note, donations tend to spike on national election years (2004, 2009, 2014, 2019). Parties ended up raising almost twice as much via electoral bonds as from disclosed donations (top panel), but from a smaller number of donors (bottom panel). Disclosed donations, on the other hand, appear to grow at the same pace as in the pre-electoral bond period. In aggregate these values are similar in magnitude to estimates of dark money spending in US elections, according to American campaign finance watchdog OpenSecrets.[13]. Examining annual audited party expense reports indicates a marked shift in aggregate expenditure by political parties in 2018, alongside

[12] See for instance Bertrand et al. (2002); Goldberg et al. (2010); Kala (2024).
[13] `https://www.opensecrets.org/dark-money/basics`

the introduction of electoral bonds. Taken together, these suggest that the introduction of electoral bonds likely changed the landscape for political finance.

Figure A3 shows that overall corporate donors make up the bulk of political donations by year across both channels—a departure from the US case, where individual donors dominate (Ansolabehere et al. 2003). Among disclosed donations there is a censoring problem that arises from the INR 20,000 disclosure threshold. Individuals are more likely to donate below the cap, meaning their donations are less likely to be captured. For the anonymous electoral bonds, there is no such problem. Electoral bonds were sold in denominations starting at INR 1,000 (roughly $12 in 2025), but fewer than 1% of all electoral bond purchases were of the Rs 1000-denominated variety, indicating little take up by individual small donors in general. Instead, almost 97% of anonymous donations came from corporations.

3.2. Characteristics of undisclosed donors

We compare donors using undisclosed donations, i.e. electoral bond buying firms, with disclosed donor firms and the overall population of firms from the MCA's registrar of registered companies. Panels A and B in figure A4 show how donors vary compared to the overall population of firms in general, and then within the choice of donation channels.

Note that some firms within the disclosed and electoral bond categories are overlapping.

Fig A4 highlight how electoral bond buyers tend to be larger, older firms and more likely to be publicly listed corporations.

3.3. Undisclosed Donation Patterns and Recipients

Figure A6 captures how strikingly different firms behave when using each donation channel. While disclosed donors tend to donate once, and to a single party, electoral bond buyers tend to donate often, in larger sums, and to multiple political parties.

As discussed in Puri (2024), the disclosed donations produce a puzzling pattern for the money in politics literature. In the broader literature on campaign finance, *individual* donors are characterized as *expressive* donors, donating sporadically in small amounts mostly ideologically to a single political party (Bonica 2014; Bouton et al. 2022), while companies tend to be more *strategic*, treating campaign contributions as investments for access and influence (Snyder Jr 1990). In a competitive, federalized, multi-party democracy such as India's, it is surprising that a strategic company, likely exposed to multiple political parties across state, national, and local levels, would donate to a single political party. While disclosed donations depict a puzzling pattern of seemingly non-strategic behavior, the hidden channel appears more classically strategic—companies participate often to donate larger sums to multiple political parties (see figure A6).

Kerr et al. (2014) study the dynamics of firm lobbying in the US and find that while only 10% of publicly listed companies lobby, they exhibit a high degree of persistence (92%) with little entry and exit year-over-year. They argue this indicates high barriers to entry which substantiates theoretical estimates of fixed costs relating to lobbying (Bombardini 2008).

While we too find that only a minority of firms participate in any form of political financing, figure A7 shows both much lower levels of year-over-year persistence overall, but also a notable persistence gap between the two channels. An electoral bond buyer in year t is 25% likely to purchase a bond again in year $t+1$, while a disclosed donor is only 10% likely to donate again the following year. This gap is likely explained by similar lobbying fixed costs described by Kerr et al. (2014), that arise from needing to send an envoy to physically purchase and deposit electoral bonds in party accounts on specific dates and in specific bank locations. This more time and effort costly procedure contrasts with the simplicity of the disclosed channel, where companies can hand over checks to party operatives at any time. And so it is reasonable that more sophisticated companies are able to overcome the entry barriers of buying electoral bonds.

What might explain this difference? Drawing on a corporate governance perspective, Puri (2024) highlights how concentrated decision-making agency within family businesses produce this pattern of seemingly non-strategic corporate giving among disclosed donations. The explanation is that family businesses tend to behave like individual donors, giving expressively and often to co-ethnic political parties—a notable feature of individual giving (Grumbach and Sahn 2020; Grumbach et al. 2020; Bouton et al. 2022). While family businesses make up the dominat share of enterprises in India, and indeed among disclosed donors, Puri (2024) finds that family businesses are less likely to take up the electoral bonds channel. This implies that since more strategic firms are participating in the hidden channel, their donations appear more strategic as well.

3.4. The private cost of making confidential donations public

For the subset of publicly listed firms, we study in an event study the value effects of the second shock from the regulatory timeline: retroactively revealing the names of all electoral bond buyers between 2019-2024. This was a highly salient news event, with journalists and commentators from global news sources covering this release. How did this affect firm value for companies on the list?

Out of the approximately 900 companies revealed to have bought electoral bonds, 106 were publicly listed entities, and 88 with shares actively traded on the National Stock Exchange (the more liquid exchange compared to the Bombay Stock Exchange).

For our main empirical approach, we follow principles outlined in MacKinlay (1997), and largely track Acemoglu et al. (2016) who study the effect of Tim Geithner's surprise appointment as Treasury Secretary in 2008 on the stock prices of connected companies.

Daily abnormal returns for each firm are calculated as per MacKinlay (1997):

$$AR_{it} = R_{it} - \mathbb{E}\left[R_{it} | X_t\right] \tag{1}$$

Where AR_{it} is the abnormal return for firm i on day t, R_{it} is the actual firm returns on day t, and $\mathbb{E}[R_{it}|X_t]$ is a benchmark expected return for firm i on day t based on conditioning variables in X_t. Expected returns are calculated using the average market return, or an estimate based on a historical relationship between the daily returns of stock of company i and market returns (CAPM), or key risk factors within the market (Factor model, such as Fama-French). Per Acemoglu et al. (2016), for each company i, we estimate a historical linear relationship between a stock's daily returns and the Nifty 100 over a one year period up to 30 days before the event date. We also calculate excess returns, which simply uses market returns as the benchmark.

Adding up abnormal returns over a given window generates a measure of cumulative abnormal returns, which we use to infer the overall effect of sudden transparency over several trading days.

Equation 2 depicts our main empirical specification.

$$y_{it} = \sum_{s \neq T-1} \beta^s \mathbb{1}[t = s] \times Donor_i + \alpha_i + \eta_t + \gamma t X_i + \epsilon_{it} \tag{2}$$

y_{it} is the abnormal daily return, or excess daily return, for firm i on day t. α_i and η_t are company and date fixed effects. $Donor_i$ takes the value 1 if the company is on the list of donors revealed on T = March 14, 2024. tX_i is a vector of firm-specific controls interacted with time dummies, with coefficients γ. $\hat{\beta}^s$ estimates the average effect of being a donor on abnormal daily returns on day s compared to the reference period. We choose to set March 13 as our reference date—one day before the event.

While α_i captures unobserved time-invariant differences in levels of returns across firms, we also include tX_i which is an interaction of firm-level characteristics with time dummies to ensure the estimates do not capture the effect of the shock on other characteristics that may be correlated with the treatment. Following Acemoglu et al. (2016) we include size, leverage, and profitability as firm-specific covariates. We also include indicators for industry groups and a measure of market capitalization a month before the event date. Appendix D shows how the probability of being a donor varies each of these characteristics. Including these interacted fixed effects implies an assumption of parallel trends conditional on these covariates. We attempt to validate this conditional parallel trends assumption visually by including several pre-periods in the event study window, and by running a placebo analysis where we set the reference period to two weeks before the actual event period. We cluster standard errors at the company level. We cluster standard errors at the stock level.

Multiplying the cumulative abnormal returns with the market capitalization of donor companies immediately prior to the event date estimates the change in corporate value associated with information release, and therefore quantifies the cost to the firm of making confidential donations public.

Figure A8 shows the main result of estimating equation 2 on an outcome variable of daily abnormal returns. Companies revealed to be politically active by buying electoral bonds saw a sharp abnormal decline on the day of the release (on average, a 1.5% abnormal decline), persisting for several trading days after. Appendix F.1 reports the results across a range of different empirical specifications, including winsorizing or trimming daily returns to ensure the results are not driven by outliers. The negative effect is consistent in all specifications, with qualitatively similar magnitudes and significance.

The pre-period shows no visually apparent trend, with most estimates in the pre-period generally not significantly separable from zero. Additionally, we run a placebo test where we replace the reference period (March 13, 2024) with one from two-weeks before the event date (February 26, 2024). As shown in appendix F.3, neither the pre-period nor the post-period show a significant and systematic difference between the two groups. These diagnostic tests suggest a strong treatment effect of the information shock, revealed on the event date.

An important detail is that the list of donors was revealed *after* market-hours on the 14th, even though abnormal daily price action is evident on the day itself. The pre-announcement decline reveals the negative effect was driven by not just the release of information, but also the *anticipation* of its release.

Even though the Supreme Court had required the list be revealed by March 6 in its original February 15 ruling, commentators remained skeptical that the State Bank of India would actually adhere to this timeline (Vaishnav 2024). This skepticism was partially vindicated when the SBI requested an extension until June 30. But the Court rejected their request, but revised the release date to be March 15. The threat of information became credible on March 12, when the SBI submitted a password-protected USB drive containing the list of donors to the Election Commission. At this point, it was clear that the ECI was going to reveal the information over the next few days, and some stocks started pricing in what was expected to be in the information release.

This market pattern is consistent with empirical studies of *pre*-announcement and *post*-announcement drift around salient market or corporate news events, like FOMC meetings (Lucca and Moench 2015), company earnings, or index inclusions or exclusions (Fernandes and Mergulhão 2016). These studies find equity markets to move in advance of information releases, despite low trading volumes, followed by a bump in trading volumes *after* the information is actually revealed (see appendix F.4)—indicating more of a retail reaction to news (Frazzini and Lamont 2007)—as well as a post-announcement drift, where prices do not correct immediately in one go, but take several days to percolate through.

Some research has tied this pre-announcement drift to private information leaks, for instance between the Fed and market participants (Cieslak et al. 2019). But pre-announcement price action does not necessarily require leaked information and could emerge from the rational behavior from market participants facing uncertainty (Cocoma 2018). More concretely in the case of electoral bonds in India, it was perhaps not a big surprise which companies were likely to be on the list of donors in the first place, with about half of the companies eventually revealed as donors previously giving through disclosed channels in any case.[14]

Figure A10 visualizes the conditional average treatment effect on each treatment arm ($\hat{\beta_G}$). Similar results between New vs Known and Low Amount vs High Amount donors point to limited heterogeneity on these dimensions, and therefore provide limited support to the mechanism of investors learning new information about donors' business models and updating their valuations accordingly.

We formally test the effect of this information release on the cumulative average returns of companies revealed to be on the list versus those companies not on the list of political donors by estimating equation **??**. Table A1 reports the conditional average treatment effect on the treated (CATT) on cumulative abnormal or excess returns across various windows of trading days after the event date. We find treated firms experience a sharp and significant underperformance on the event day (March 14) and over the following week relative to normal expectations and the overall market. More precisely, over seven trading days after the information release, treated firms experience, on average, a 2pp cumulative abnormal underperformance versus non-treated firms. This significant negative effect only lasts up to 7 trading days, after which the difference between treated and non-treated firms starts to reduce.

As a robustness exercise, we implement an alternate procedure, synthetic control method, that compensates for potential violations in parallel trends. A difference-in-difference approach assumes parallel trends between treatment and control groups hold after including covariates and firm-fixed effects to capture unobservable characteristics. The synthetic control method compensates for potential violations of parallel trends by reweighting units to match pre-treatment trends (Arkhangelsky et al. 2021). Developed by Abadie and Gardeazabal (2003); Abadie et al. (2010, 2015), this process involves constructing a synthetic version of each treated unit based on all control unit outcomes, weighted by its fit in the pre-treatment period, and is sometimes used as a robustness test for difference-in-difference procedures.[15] We follow Acemoglu et al. (2016), given its similar setting of multiple treated units, and aggregate treated firms' actual returns deviations from their synthetic counterfactuals. We estimate confidence intervals using permutation tests as recommended by Abadie et al. (2010); Abadie (2021). We provide detailed descriptions of the process in appendix H.

Estimating the cost of revealing political connections. As of March 13, 2024, donors constituted approximately 5% of all publicly listed and actively traded companies on the NSE, but accounted for close to 14% of the overall market capitalization of over $4 trillion, i.e. $609 billion.

[14] For instance, the financial presses reported Adani enterprise stocks experiencing a sharp selloff in anticipation of the release of the electoral bond buyers, with the conglomerate reported to have close ties to the government (Iyengar 2024).

[15] See for instance Acemoglu et al. (2016); Mirenda et al. (2022)

A 2% abnormal decline over 7 days on a market capitalization of $609 billion implies a value destruction in the order of $12 billion that can be traced to the sudden revelation of companies' political participation. For context, the entire electoral bonds scheme raised a total of $1.7 billion (Traveli and Kumar 2024), making the short-term cost of revealing political connections more than 5 times the actual benefits transferred to the political parties, and over 100 times what these specific companies donated.

Over the long-run however, the effect is more muted, with cumulative abnormal or excess returns of treated and non-treated firms indistinguishable after 10 days.

We replicate these findings in direction, magnitude, and duration of effect using a synthetic control approach (appendix H.1).

4. Rationale for using confidential donations

Why would a firm seek to hide its political activities? While journalistic and academic accounts clearly show that firms actively seek to obscure their political activities through hard-to-trace channels (Durkee 2017; Hertel-Fernandez 2019; Bertrand et al. 2020), the reason is not obvious. In fact, given the weight of evidence that finds firms *benefit* from political connections (Faccio 2006), it would appear they might stand to benefit from publicizing their politics. Despite the balance of scholarly evidence that finds returns to political connections, a burgeoning literature finds political connections to be a double-edged sword (Siegel 2007; Borisov et al. 2016; Bertrand et al. 2018; Bhandari 2022).

To understand why a firm may choose to hide, it is useful to consider who a firm might be hiding *from*? We consider three sets of audiences that a firm want to shield its political activities from: other political parties, customers, and investors.

4.1. Hiding from whom?

Hiding from parties. Firms may choose to hide their political contributions in order to avoid antagonizing rival political parties. In highly competitive political systems, donations to one party can brand a firm as partisan, leaving it vulnerable to retaliation should a different party come to power. This concern was a central justification for the introduction of the electoral bonds scheme: government officials explicitly stated that anonymity was needed to protect donors from vindictive treatment by opposing parties once they assumed office. The strategic incentive for anonymity, then, is not simply about obscuring favoritism but also about avoiding punishment.

To operationalize the strategic motivation for hiding from rival parties, we construct measures of each firm's political exposure during the post-electoral bonds period (2018–2024). Our main measure captures the extent a company is exposed to multiple political parties, and counts number of unique political parties a firm is exposed to based on its geographic location. A firm is considered exposed to a party if that party holds power in the state where the firm is headquartered or at the national level (where the BJP held power throughout this period). This count captures the firm's potential incentives to avoid being seen as partisan by other ruling entities. An alternate measure is a binary measure indicating whether a firm is exposed to any non-BJP party at the state level. The logic behind this measure is that if a firm is only exposed to the BJP and donates exclusively to the BJP, then it faces little threat of retaliation from rival parties—thereby reducing the need for secrecy. In contrast, firms with cross-party exposure may perceive greater political risk in publicly aligning with a specific party and therefore have stronger incentives to route donations through anonymous channels.

Hiding from customers. Firms may also choose to hide their political activities to avoid alienating customers. A growing body of research suggests that political affiliations can shape consumer behavior in meaningful ways. On one hand, partisanship itself can drive customer reactions: consumers may punish firms for aligning with parties or candidates they personally oppose (Panagopoulos et al. 2020; Conway and Boxell 2024). Even apart from ideological commitments, customers may view politically connected firms with suspicion, perceiving them as less reliable or merit-based market participants (Bhandari 2022). In this view, political entanglements may threaten a firm's commercial legitimacy, especially in consumer-facing industries. Hiding political contributions, then, can be a strategy to maintain political access while minimizing the risk of alienating their customer base. This theory implies, therefore, that companies in *consumer*-facing industries face greater incentive to veil their political activities.

In order to measure how consumer-facing a company is, we follow Kisat and Phan (2020) and use a measure of how upstream the industry is in the global value chain, based on its industry code. "Upstreamness," standard in trade and network literature, captures a "distance from final use" (Antràs et al. 2012), and is measured at the industry-level using a country's input-output table. In brief, the gross output Y of each industry j is defined as the sum of its final goods (F_j) and intermediate goods (Z_j) that are used as inputs in other industries $\neg j$. Z_j can then be disaggregated as all the dollar amount of industry j's output that is needed to produce industry k's output (Y_k), summed over all industries $k \neq j$. This quantity can similarly be disaggregated into an infinite sum of its inputs further along the supply chain.

$$Y_j = F_j + Z_j = F_j + \sum_{k=1}^{N} d_{jk} Y_k = F_j + \sum_{k=1}^{N} d_{jk} F_k + \sum_{k=1}^{N}\sum_{l=1}^{N} d_{jk} d_{kl} F_l + \ldots \tag{3}$$

An industry's upstreamness U_j is measured then as the sum of each of the terms in equation 3 multiplied by its distance from final use and divided by Y_j:

$$U_j = 1 \cdot \frac{F_j}{Y_j} + 2 \cdot \frac{\sum_{k=1}^{N} d_{jk} F_k}{Y_j} + 3 \cdot \frac{\sum_{k=1}^{N} \sum_{l=1}^{N} d_{jk} d_{kl} F_l}{Y_j} + \ldots \tag{4}$$

This produces an intuitive result where $U_j \geq 1$ and when U_j is close to 1 it is more downstream and consumer-facing (e.g. automobiles and footwear sectors) and for higher values, the industry is farther away from being consumer facing (e.g. petrochemicals and refining of copper).

Antràs and Chor (2018) compute and share a measure of upstreamness for 4-digit ISIC industries for 41 countries at various points of time using the World Input Output Database.[16] As India is not one of the countries, we use the measure of upstreamness for the catchall Rest of World category. We also use upstreamness based on the United States as a robustness check—these two measures are highly correlated (see appendix C).[17]

Hiding from investors. Just as companies may worry about alienating consumers, they may fear backlash from investors who see political maneuvering as a red flag (Borisov et al. 2016). Even when legal, corporate political donations can appear unscrupulous or risky to institutional investors, especially in environments where such contributions are widely viewed as synonymous with corruption or favoritism. Another reason why firms may hide from investors is more strategic: managers may want to preserve the narrative that firm performance is driven by operational excellence, rather than political proximity. Public revelations of political giving risk muddying this story, and open up firms to investor suspicion that strong performance is the result of rent-seeking rather than market competitiveness. This reason relates to much work in finance on signal jamming between managers and owners (Holmström 1999; Niessner 2015).

We operationalize investor scrutiny by simply identifying if a company is publicly listed or not. Firms with shares trading publicly on exchanges are subject to greater regulatory and investor scrutiny, through quarterly and annual shareholder meetings. While privately held companies may too have external investors, the MCA does not record and make publicly available details of firms' capitalization table. Regardless, most formal businesses are privately owned by a single family, or sole entrepreneur, and do not have external investors to cater to (or hide from).

Empirical Approach. To study how each of these three factors may affect a firm's decision to take up electoral bonds, we construct a firm-level dataset, and add an indicator that takes the value 1 if the firm i ever purchased electoral bonds between 2018-24, and 0 otherwise. We then regress this outcome measure on with each of these measures: multi-party exposure, upstreamness,

[16] We access this measure through the `concordance` package in R (Liao et al. 2020).

[17] In future versions we shall use Kisat and Phan (2020)'s measure of upstreamness calculated using Input-Output tables from India's Ministry of Statistics and Programme Implementation. We thank Faizaan Kisat for sharing his files for this.

and public listing, sequentially adding controls for age, size, industry and state of registration fixed effects. Equation 5 presents the fully saturated specification:

$$y_i = \beta_1 \text{Measure}_i + \beta_2 \text{Age}_i + \beta_3 \text{Size}_i + \gamma_i + \eta_i + \epsilon_i \tag{5}$$

where $y_i \in \{0, 1\}$, and γ_i and η_i indicate state and industry fixed effects. We estimate this model using OLS and calculate heteroskedasticity-robust standard errors. Note, these measures of multi-party exposure and upstreamness are defined at the state and industry-levels respectively, meaning they are not estimable in the fully specified regression.

We run this regression first on the full population of firms in the MCA, estimating an unconditional likelihood that a firm takes up this hidden channel. Next, we subset to firms that donated in the year 2018 and onwards—this captures the fact that during this period, firms had a choice to make about making a disclosed or non-disclosed donation.

A theory of firms hiding their politics from other parties would predict a $\hat{\beta} > 0$ for a measure of multi-party exposure. A theory of firms hiding their from customers would predict a $\hat{\beta} < 0$ for a measure of upstreamness. And a theory of firms hiding from their investors would predict a $\hat{\beta} > 0$ for publicly listed firms.

Figure A11 presents the results. Across both sets of regressions, firms' status as being publicly listed is the strongest predictor of take up of this hidden channel of giving.

4.2. Substituting from disclosed to undisclosed donations

How does the introduction of this new channel cause a company to reconsider its overall donation strategy? A body of work studies how corporate charitable giving and political giving may be substitutes (Yildirim et al. 2024), and so we examine whether electoral bonds are complements or supplements to the disclosed channel already available. Given that publicly listed companies are most likely to take up this channel when it becomes available, we study how they rebalance their portfolio of political giving after electoral bonds become available in 2018.

For this, we construct a balanced panel of all potential donor firms for every year from 2014 to 2024. We restrict our sample to all "ever donors", i.e. companies that have ever made a donation across either electoral bonds or through disclosed donations to ensure comparability, and that were founded before 2014 to ensure no survival bias. We flag all corporations that were publicly listed before 2018 as "treated" and non-publicly held corporations as controls. We aggregate annual data of donations via electoral bonds and disclosed at the firm-year level, and sum the two amounts to arrive at a total donated amount. We also calculate a bond share of total which is the annual donations made via electoral bonds divided by the total donations made overall.

Using a difference-in-difference event study, we examine how the donation strategy of firms that were publicly listed firms evolve in response to the introduction of electoral bonds in 2018.

We estimate the following event study specification:

$$y_{it} = \alpha_i + \gamma_t + \sum_{s \neq 2017} \beta_s D_i \cdot 1[t = s] + \epsilon_{it} \tag{6}$$

where y_{it} is the outcome variable: total donated, total donated via disclosed donations, total donated via electoral bonds, and the electoral bond-share of all donations made by a company i in year t. D_i is the treatment, and takes the value 1 if company i is a publicly held corporation over the entire period.

Figure A12 shows how after the introduction of electoral bonds in 2017, publicly held corporations were clearly more likely to take up the new channel, and substituted away from the disclosed channel, leaving the total donated amount roughly unchanged (except for a spike for the 2019 elections). This result suggests that hidden channels are more substitutes than complements for publicly listed firms.

It is worth noting how these two sets of results about the behavior of publicly listed firms impact the broader money in politics literature. Due to data limitations, most studies on corporate campaign finance are restricted to publicly listed companies. Benefiting from being able to access all firms in the formal sector in India, we can show how publicly listed firms behave systematically differently from non-listed entities, and actively seeking to obscure the extent of their political giving.

4.3. Close elections and multi-party hedging

In a competitive, multi-party federal democracy, politically active firms are incentivized to hedge their bets by donating across multiple political parties. But such a strategy risks political retribution in the event a party comes to power and punishes opponent supporters. Opacity, therefore, reduces the retribution risk firms face when deciding to openly donate to multiple parties.

We show evidence that firms may be choosing to hide their political donations out of fear of political retribution in two ways. First, in aggregate, despite the BJP's single-party dominance, at least at the national level, during the entire period of electoral bonds (2018-24), the BJP received less as a share of total opaque donations than disclosed donations. This extends to the concentration of political party recipients in general as well. See figure A13.

Second, we use elections as sharp instances when companies are more likely to need to hedge their bets, ahead of political political changes. Using around 100 state-level elections, we examine the donation behavior of firms headquartered in poll-bound states six months prior to the elections. We compare the likelihood companies donate to multiple political parties during this election period across close and non-close elections—as defined by assessing if the mean margin of victory (MOVs) in each of the single-member districts in the state in that election is below the overall median of mean MOVs. See appendix E. Figure A14 shows how compared to disclosed donors, opaque donors are more willing to make multi-party donations during election times in general, and especially around close elections. Disclosed donor hedging behavior appears less sensitive to the political risk of election closeness.

5. What drives the negative effect of revealing political activities?

What drives the value destruction that comes from revealing a firm's political donations? We consider two mechanisms: investors re-rating a company's fundamentals in light of new information; or a more reputational story of investors punishing firms for being embroiled in political scandal.

Fundamental Updating. If information about political activities is salient for investors' assessment of the fundamental value of a company, then the effect of the release should depend on how much the information shifts prior beliefs about the company's political activities. Managers may have chosen to suppress this information from investors,[18] and given the scheme required no disclosure either publicly or in annual filings, revealing the list of donors may have had potentially high informational content.

The March 14 release delivered two sets of information: the *fact* that a company made political donations, and the *extent* of its political donations, measured by the total amount donated. Either of these pieces of information could be *surprising*, and prompt an equity analyst to update her beliefs about the health of the company, and its prospects for future cash flow. For instance, learning about a company's political activities might indicate the company's reliance on these electoral bonds to win contracts, which is no longer available. We label this the *fundamental updating* channel.

Reputational Cost. Reputation plays an important role in shaping a company's valuation and performance (Tadelis 1999; Lange et al. 2011). Closely related is the role of the media in facilitating an information flow between the general public, investors, and companies (Graf-Vlachy et al. 2020). Financial newsmedia act as monitors of corporate governance, evaluating whether companies run afoul of broad social values (Bednar 2012; Dyck and Zingales 2002), and shapes how the public perceives companies. In turn, a company sees its reputation in the media as a "strategic resource" to manage (Deephouse 2000).

Given a general perception of corporate political activity being synonymous with corruption and special interest (Nyberg 2021), a highly publicized release of political donors would threaten negative news coverage and engulf these companies with air of scandal. Indeed, the days after the event, Indian media outlets were abuzz with coverage of the top donors, and muckraking potential *quid pro quo* arrangements between the state and these donors.

A quantitative examination of the news coverage confirms that the media regarded electoral bonds as a matter of corruption. We use `newsapi.org`, a third party data provider that aggregates news articles from over 150,000 online sources around the world, to gather all English-language news reports from India from Jan 1, 2024 to April 30, 2024 about electoral bonds, and

[18] "Signal-jamming" in managerial economics describes how managers may manipulate information that investors rely on to price the company (Stein 1989; Holmström 1999; Niessner 2015)

a baseline reference of India political news during the same period. We first show in panel A of figure A15 that coverage of electoral bonds spikes around key events: February 15 Supreme Court judgement and March 14 data release. We then examine how the electoral bonds story was covered by comparing how frequently specific terms were used versus the reference period—standard practice for researchers looking to compare two corpora of text.[19] We use term frequency inverse document frequency (TF-IDF) that helps filter out both extremely common and extremely rare words (Gentzkow et al. 2019), and construct a ratio of TF-IDF for each term in electoral bond news to the same in the reference news. Panel B in figure A15 shows how terms like `extort`, `corrupt`, `scam`, `bribe`, and `black` [money] are much more likely to be used in electoral bond coverage. We provide further details and results in online appendix I.1.

[BV: would be interesting to see if the market is predicting well at the SC decision who was doing it. Could also be a falsification test for the fact that the information was already out there.]

In order to directly test each of these alternate mechanisms—fundamental updating and reputational cost—we split the 88 donor firms into treatment arms, leaving the full set of non-donors as controls.

Fundamental Updating. The mechanism of investors updating their beliefs about a company's corporate fundamentals requires separating companies by the *kind* of information that was revealed on March 14. We consider both the extensive margin of political participation (i.e. learning *that* a company is politically active), and the intensive margin of political participation (i.e. learning about the *scale* of its political activities).

Out of the 88 publicly listed companies revealed to be buyers of electoral bonds, we find 48 had also made donations at some point through disclosed channels, while 40 did not.[20] This means for the 48 companies that had at some point made donations through a publicly disclosed channel, learning the fact that they also gave via electoral bonds would not cause investors to update their beliefs about the political participation of these firms. On the other hand, for the 40 companies newly revealed to be politically active, the market may be learning new signals about the company, like the importance of political connections for its business model, or the health of the business that might be driving it to seek out political connections in the first place. We assign the 48 known-donors to the "Known Donors" treatment arm, while the rest to the "New Donors" arm. A mechanism of investors updating beliefs about the fundamental value of the business based on this news would predict a difference in treatment effect across these treatment arms.

The *extent* of political activity may also cause investors to update their fundamental valuation of the company. Being a large contributor might also signal the importance of political

[19] See for example Rayson and Garside (2000); Groseclose and Milyo (2005); Caldara and Iacoviello (2022)

[20] We search for these companies in the entire period of recorded disclosed donations (2003-2022). Only 30 companies gave through disclosed channels from 2018 onwards, indicating a substitution from the disclosed to covert channels once the electoral bond scheme commenced.

connections to a company's operations, and therefore raise concerns about the future viability of the business model after the end of the electoral bonds scheme. We therefore split the treated groups into "High amount" and "Low amount" treatment arms based on the total amount donated compared to the median amount donated by these firms.[21] The expectation here is that firms putting more money into political connections should be more materially affected by the light shone on its past activities and on its business prospects moving forward, predicting a difference in treatment effect across treatment arms.

Reputational Cost. The reputational cost mechanism is less about investors updating their evaluations about a company's business model moving forward, but more a reaction to a high profile political scandal. This may have long-term knock-on effects on the health of the business moving forward, but is more immediately influenced by public attention. We test for this in two ways.

First, for a direct measure of media attention, we count the number of news articles that mentions both donor companies as well as "electoral bonds" in India from March 14-28, 2024. This data comes from `newsapi.org`. Appendix I.1 presents the distribution of news mentions by donor company. We compare each company's mentions to a median measure, and classify each donor company into a "Low Media Coverage" or "High Media Coverage" treatment arm accordingly.

While this measure of media mentions is precise, it might suffer from false negatives. There may be other sources not covered in `newsapi.org`'s dragnet, especially social media sources, or companies may be mentioned by acronyms and not its official name. Therefore, we consider corporate size as an alternate proxy measure for media attention, and split treated companies by the size of its assets. This channel operates on the assumption that larger firms tend to receive more attention from the media in the first place (Deephouse 2000; Dyck et al. 2008), which makes them more vulnerable to reputational costs that might emerge from a public scrutiny. As a result, larger firms should experience a greater negative effect as a result of a sudden media spotlight on their political activities. We therefore sub-classify treated firms into "Large firm" or "Small firm" treatment arms according to the median firm size by asset value.

Empirical Approach. Appendix table A2 summarizes each of the treatment arms. We then estimate equation 7, which is a straightforward modification of equation **??**, for each set of tests, where the outcome variable is cumulative abnormal returns over 7 trading days from the event date. We keep the control group of non-donors constant, and vary the treatment group to be each treatment arm, G, thereby estimating the key coefficient of interest β_G for each treatment arm. So, for instance, in the New vs Known donor treatment condition, we estimate the average treatment effect of being revealed as a donor on newly revealed donors ($\hat{\beta}_{G=New}$) and on donors

[21] The median amount donated by these 88 firms is 100 million INR ($1.2m at the 2024 exchange rate.)

who have been revealed to be donors elsewhere ($\hat{\beta}_{G=Known}$). We cluster standard errors at the firm level.

$$CAR_{it} = \alpha_i + \delta_t + \gamma t X_i + \beta_G Donor_{it}^G + \epsilon_{it} \tag{7}$$

On the other hand, both the direct measure of media coverage (high media mentions) as well as the proxy measure (large firms) correspond to much stronger effect sizes, suggesting the overall treatment effect is driven by a firms under greater media scrutiny. In magnitude, companies facing direct media coverage about their electoral bonds saw on average a negative and significant 3.5% abnormal decline over the next 7 trading days, while companies not directly covered by the media experienced approximately null abnormal effects. This result is therefore more consistent with a mechanism of public scandal, where firms suffer short-term reputational damage as a result of being in the public limelight.

Further evidence of this reputational cost mechanism is the fact that the effect is short lived and heterogenous effects largely disappear in 10 days. Ultimately, the actual amounts contributed by these companies is likely too small to be materially consequential for the company's long term operations. For context, the total stock of donations made by the median company in this treatment group of publicly listed donor companies is just over 0.1% of its average *annual* revenue over the period of the electoral bonds scheme (the maximum is donations amounting to 5% of average annual revenue). On the other hand, as panel A in figure A15 shows, revealing the identities of donor companies did capture considerable media attention in the short-run, which would have put these firms' political activities in the spotlight during that period. Taken together, these facts support a more behavioral response where investors react negatively to learning about corporate political activities in the short-run. We replicate the same short-run heterogenous effect dynamics using synthetic control methods as well (see appendix I.3).

6. Conclusion

This paper exploits India's electoral bonds scheme to provide the first comprehensive account of corporate dark money. Anonymous donations dwarfed disclosed contributions two-to-one and attracted fundamentally different participants: larger, publicly-listed firms that donated strategically to multiple parties rather than sporadically to single parties. The data reveal that when firms can hide, they behave like the strategic political actors theory predicts—not the expressive donors that disclosed data suggest.

The market's reaction to sudden transparency was swift and severe. Donor firms lost $9 billion in market value—five times the total funds raised through electoral bonds. This punishment stemmed from media-driven reputational damage, not fundamental reassessment, evidenced by losses concentrated among high-coverage firms and rapid recovery within ten days. The magnitude of these losses explains why firms pay substantial costs to keep political activities hidden.

These results carry important implications for both scholarship and policy. For scholars studying corporate political activity, our findings highlight that visible “hard money” contributions likely represent only a fraction of total corporate political engagement and may systematically differ from hidden channels in ways that bias our understanding of firm political strategies. The fact that more sophisticated firms preferentially select into hidden channels suggests that studies focusing solely on disclosed contributions may underestimate the extent and strategic nature of corporate political influence. For policymakers, our evidence demonstrates that transparency requirements impose real costs on political actors—costs that may be necessary to maintain democratic accountability but that also create powerful incentives for circumvention. The Indian case shows how even well-intentioned attempts to create anonymous giving channels can undermine transparency without eliminating the underlying reputational and political risks that drive firms to seek opacity in the first place.

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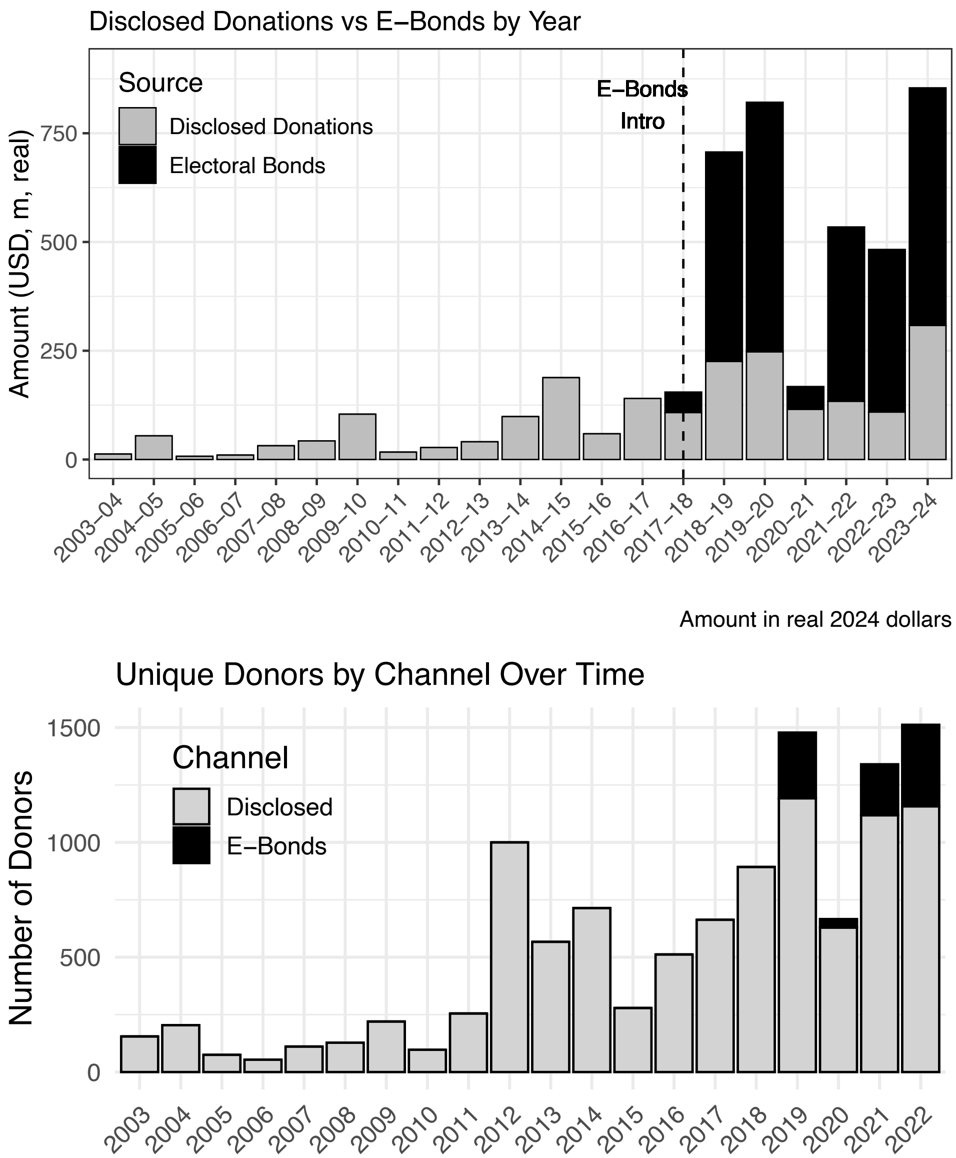
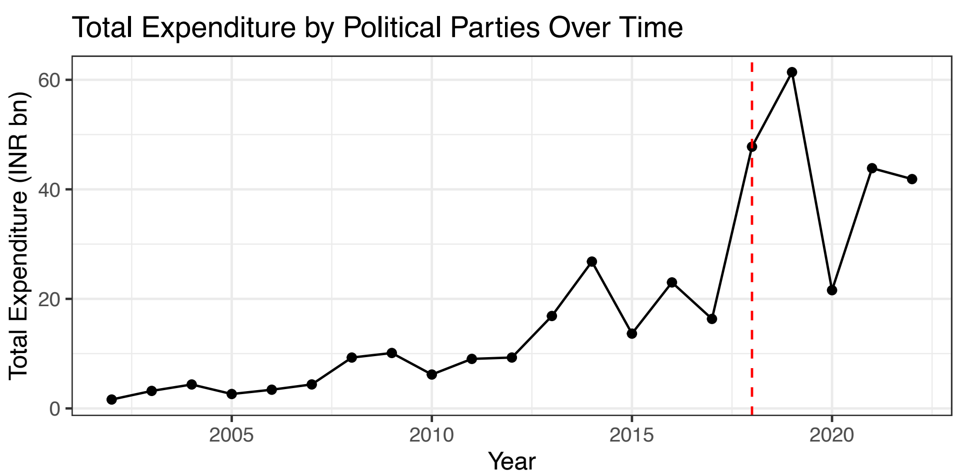
FIGURE A1. Party Finance By Source



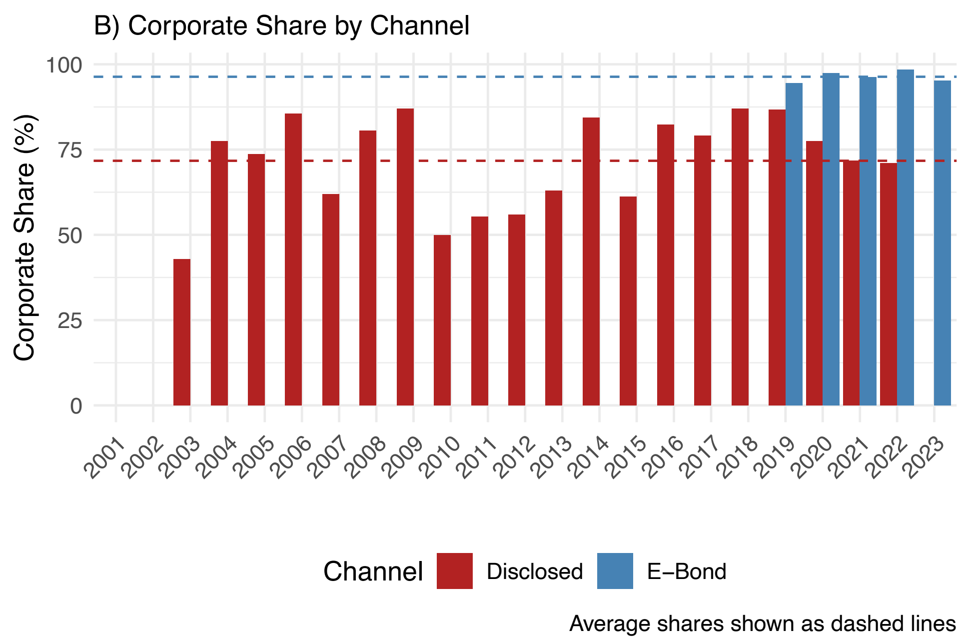
Note: The top figure compares total donations by channel by fiscal year (April to March) and shows how electoral bonds far outstripped the disclosed channel as a funding source. The bottom figure counts the number of unique donors across each channel. Together, the figure shows that while electoral bond donors are few, they make outsized contributions to party coffers. Source: ADR, Author's calculations using average annual USDINR exchange rates.

FIGURE A2. Party Expenditure Over Time



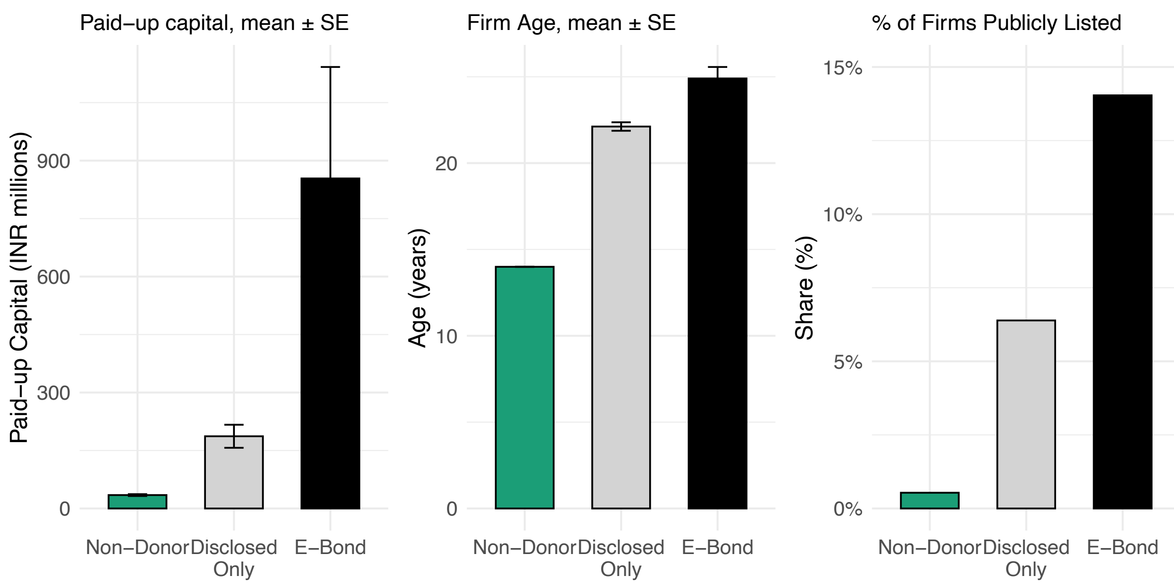
Note: The figure shows political parties' reported annual expenses, with the red dashed line indicating the introduction of electoral bonds. Aggregate party expenditures tends to spike in national election years (2004, 2009, 2014, 2019), but 2018 shows a sharp rise in party expenses despite being an off-election-cycle year.

FIGURE A3. Corporate Participation in Disclosed vs Hidden Campaign Finance Channel



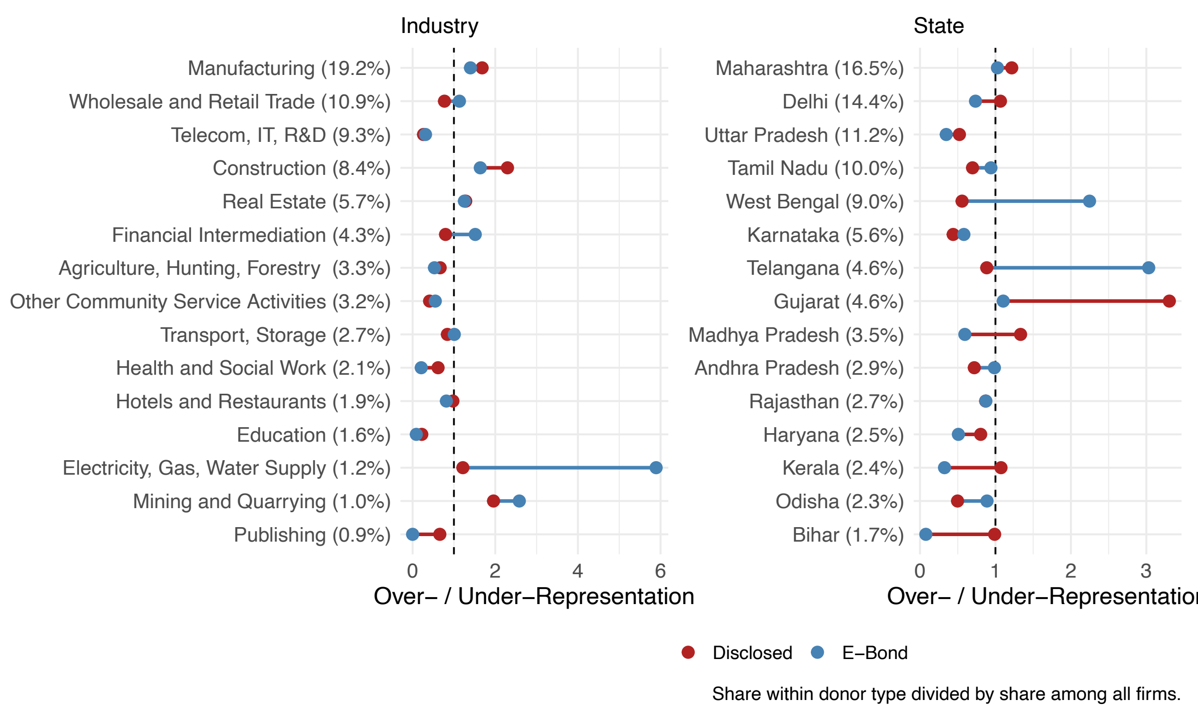
Note: This figure presents the corporate donations as a share of the annual amounts raised each year. Corporate donors defined using a set of corporate key words (like "pvt ltd" or "enterprise"). Each year corresponds to the start of the fiscal year, i.e. "2019" refers to the period April 1, 2019 – March 31, 2020. Overall, while corporate giving dominates overall campaign finance, corporate giving almost fully captures donations via hidden electoral bonds.

FIGURE A4. Comparing characteristics of electoral bond purchasers with disclosed donors and overall firm population.



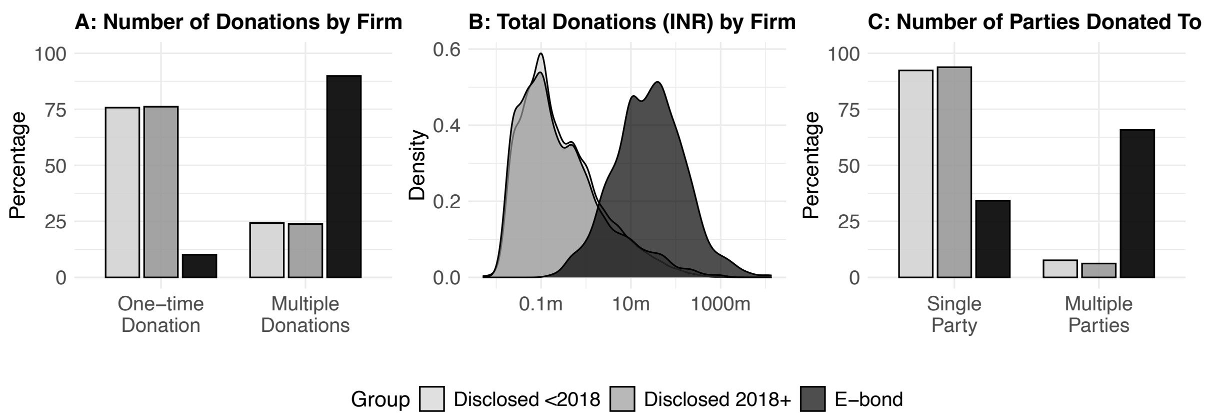
Note: The figure displays average size, age, and public listing status across the overall population of firms, disclosed donors and electoral bond buyers.

FIGURE A5. Industry and state representation (top 15 industries and states)



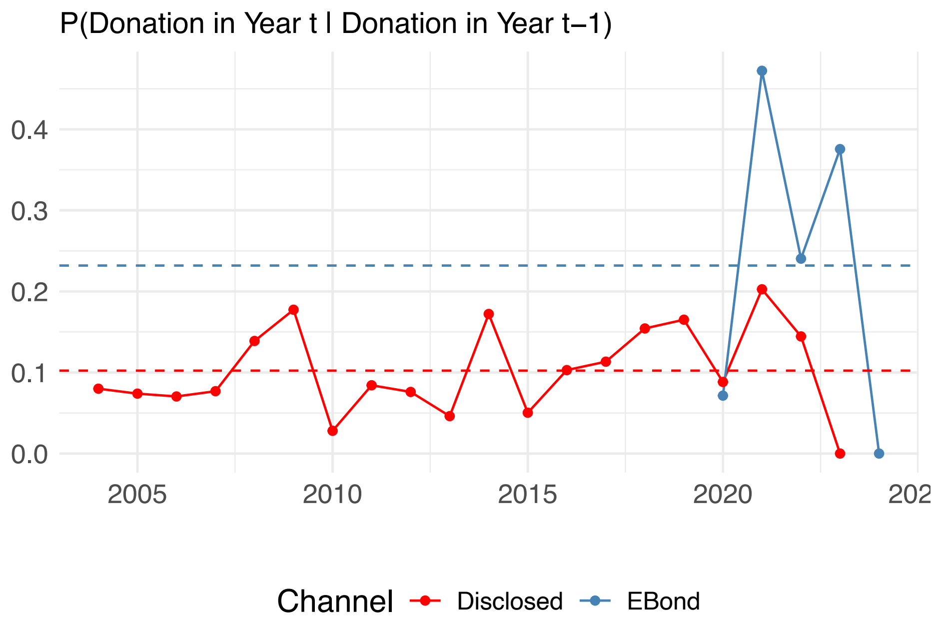
Note: Figure compares industry and state over-/under-representation relative to the formal sector. Percentages in parentheses show share in the firm population. Values >1 imply over-representation, <1 imply under-representation.

FIGURE A6. Donation patterns: opaque vs. disclosed



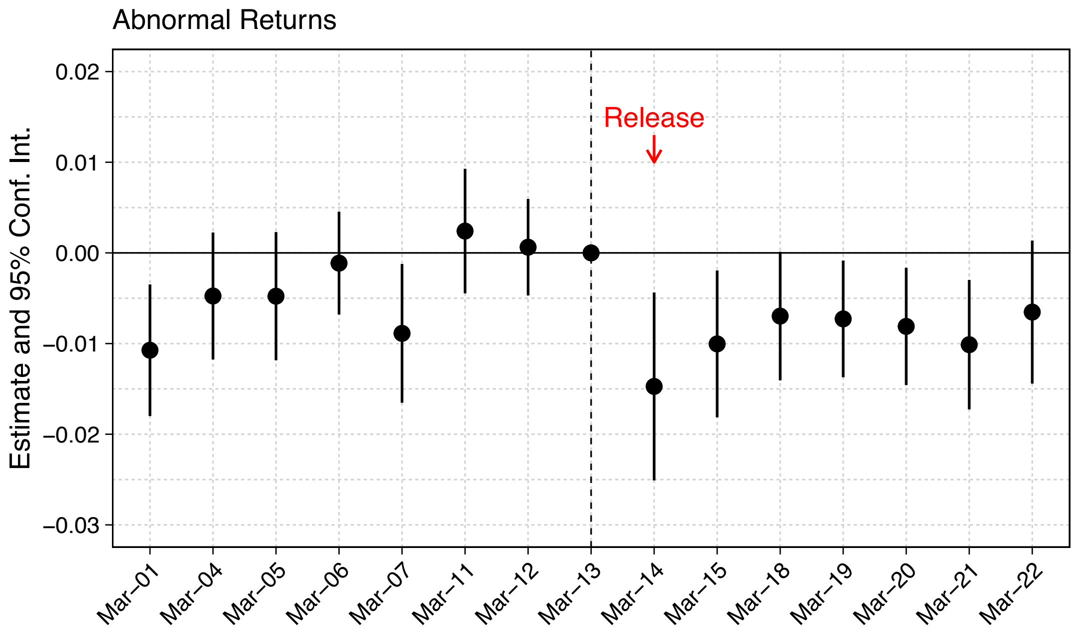
Note: This figure shows how donation firms' donation strategies differ by channel. Panel A shows the distribution of number of donations made by each firm. Panel B shows the distribution of total donated amounts across all firms. Panel C shows the distribution of number of parties each firm donated to. The charts distinguish between disclosed donation behavior pre- and post-the introduction of electoral bonds in 2018. Opaque donors donate more often, in larger amounts, to more parties.

FIGURE A7. Donation Persistence Gap By Channel



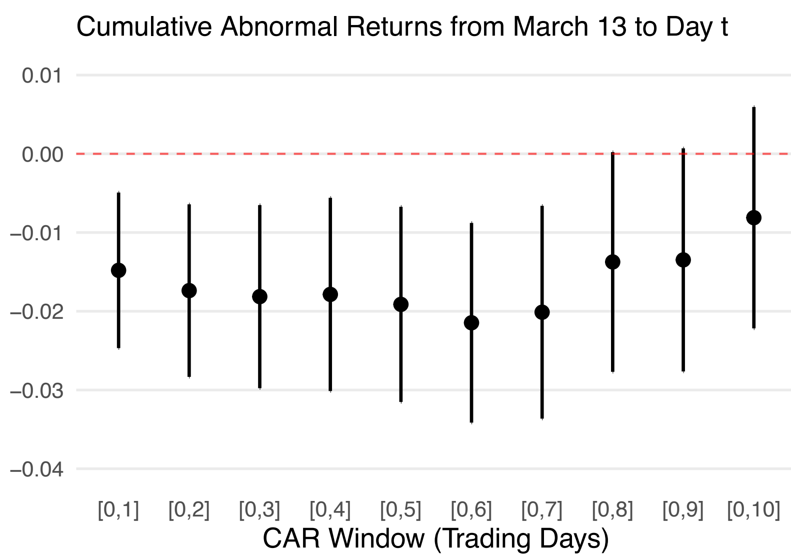
Note: This figure shows year-over-year persistence in donation by firm, i.e. what proportion of firms that donated in year $t-1$ also donated in year t. Dashed lines indicate averages by channel. Unlike in Kerr et al. (2014), the persistence of lobbying is lower overall, but electoral bond participants are stickier.

FIGURE A8. Event Study: Daily Abnormal Returns



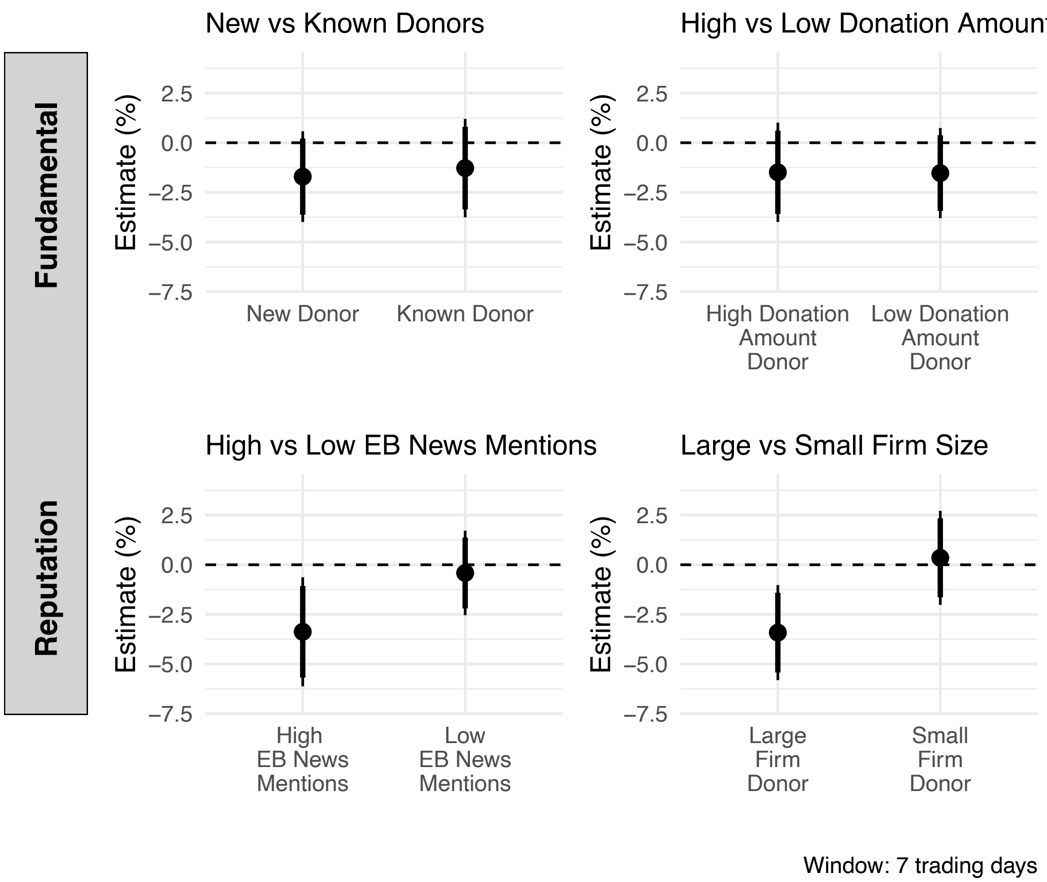
Note: OLS estimation of equation 2. Outcome variable: abnormal returns, defined as the difference between a stock's actual daily returns and predicted returns based on the market's daily return and one year's relationship between the stock and market returns. Error bars represent 95% confidence interval. Size, leverage, return on equity, market capitalization (as of Feb 15, 2024) and industry sections all interacted with time dummies. Names of donors released on March 14.

FIGURE A9. Cumulative Abnormal Returns After Revelation



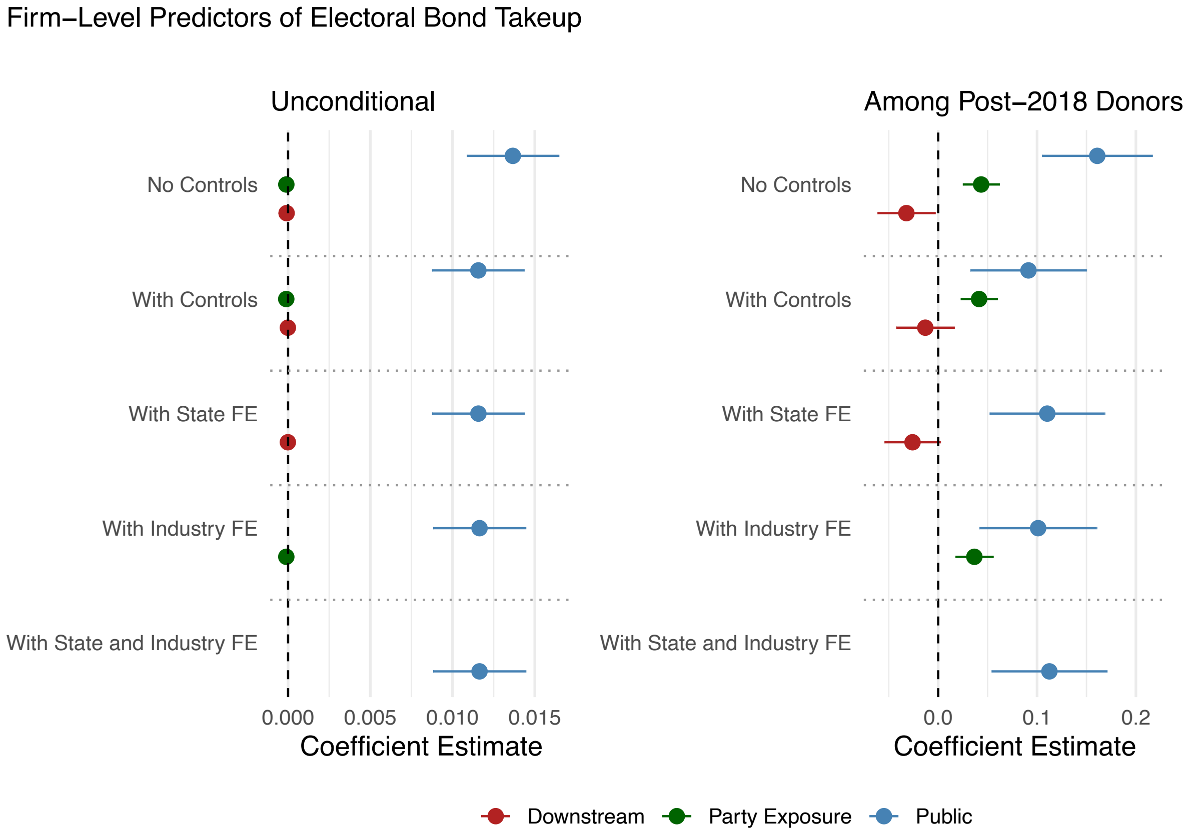
Note: This figure presents the coefficients on being a treated firm (i.e. on the list of previously-hidden donors) on various windows of cumulative abnormal returns (CAR) starting from the event date (March 14) to 10 days following.

FIGURE A10. Conditional ATT: Cumulative Abnormal Returns by Treatment Arm



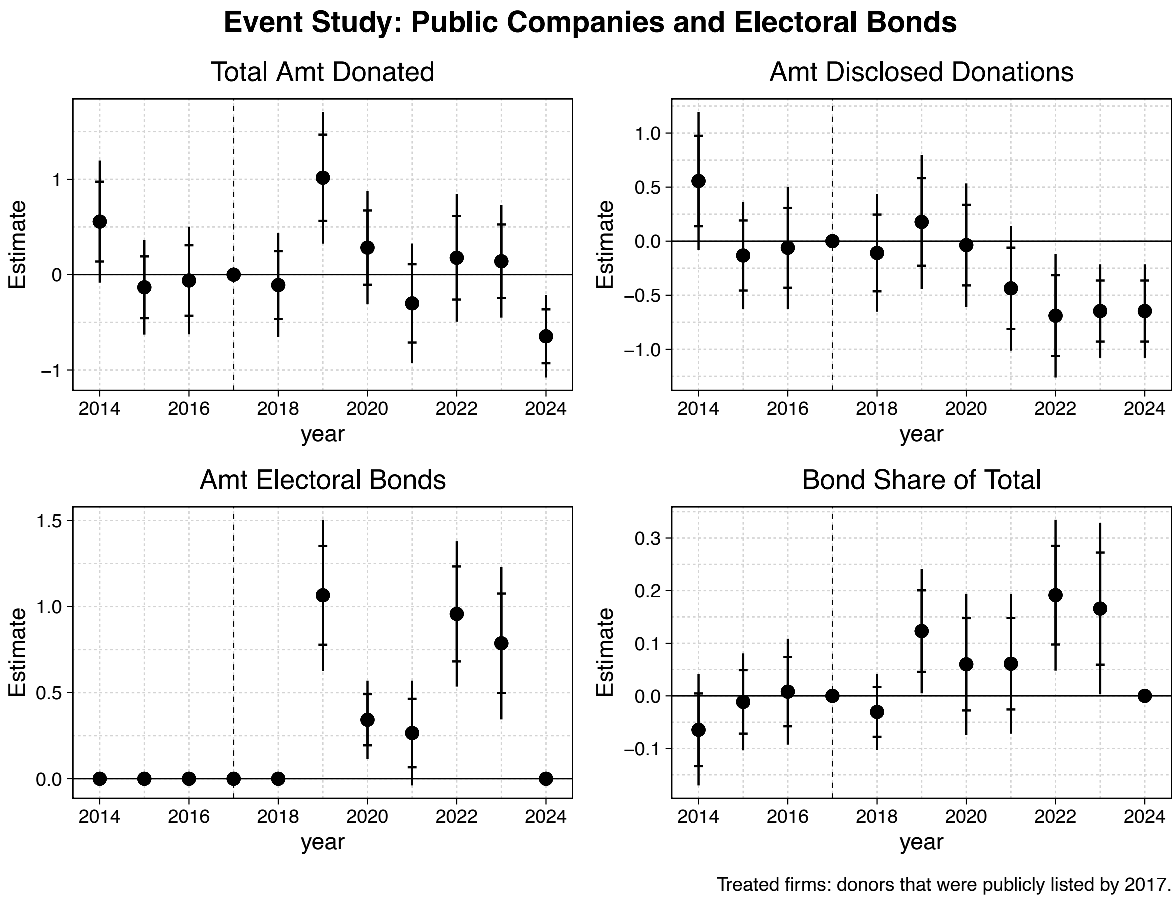
Note: Outcome variable: 7-day cumulative abnormal returns. Plots present the marginal effect of each treatment arm against a control of non-donors. Thin and thick bars reflect 95% and 90% confidence intervals respectively.

FIGURE A11. Predictors of Electoral Bond Takeup



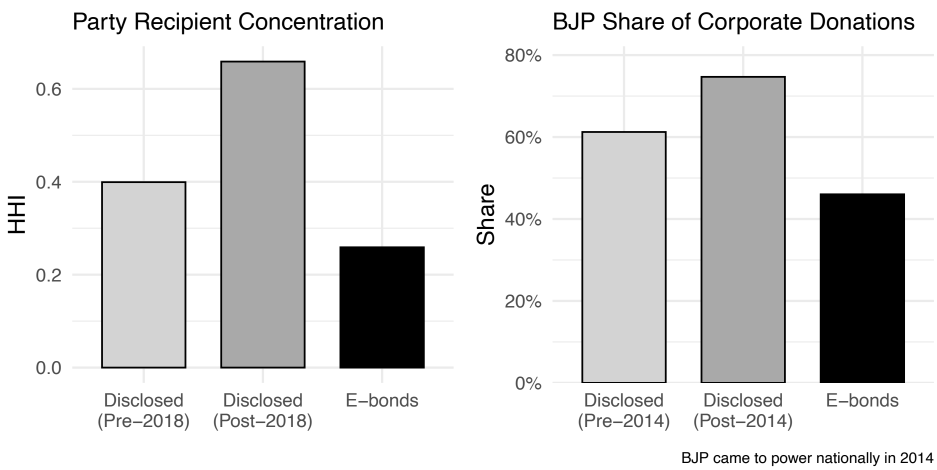
Note: This figure presents the results from estimating regression 5 ($y_i = \beta_1 \text{Measure}_i + \beta_2 \text{Age}_i + \beta_3 \text{Size}_i + \gamma_i + \eta_i + \epsilon_i$), plotting the coefficient estimates of each measure ($\hat{\beta}_1$) which captures the type of audience firms may hide from. "Party Exposure" is a count of number of parties a firm registered in a state might be exposed to. This captures the incentive of a firm to hide from other retributive political parties. "Upstream" is Antràs et al. (2012)'s continuous measure of a firm's industry's distance from consumption. This captures how sensitive a firm might be to consumer boycott. "Public" is a binary variable for whether a firm has shares that trade on the public markets, capturing sensitivity to investor scrutiny. Overall, being a publicly listed company strongly predicts take up of electoral bonds.

FIGURE A12. Publicly Listed Firms Substitute Away from Disclosed to Hidden Channel



Note: This figure studies how publicly listed firms react to the introduction of a new hidden campaign finance channel. It presents estimates from the event study specification in equation 6 ($y_{it} = \alpha_i + \gamma_t + \sum_{s \neq 2017} \beta_s D_i \cdot 1[t = s] + \epsilon_{it}$). Outcome measures compare total amounts donated, and split across disclosed and non-disclosed channels each year. The sample is restricted to "ever-donors," i.e. companies that may have donated at some point during the entire period, to ensure comparability. The treatment (D_i) is 1 if a firm i was publicly listed by 2017.

FIGURE A13. Party Recipient Differences



Note: This figure shows how opacity changed firms willingness to hedge donations across multiple political parties. The left panel shows the concentration of donation recipient parties across disclosed and opaque channels—electoral bonds were spread more evenly across parties. The right panel focuses specifically at the BJP, which has dominated national politics since coming to power in 2014, and yet received less a share of donations under opacity than disclosed.

FIGURE A14. Multi-party Hedging Around Close Elections

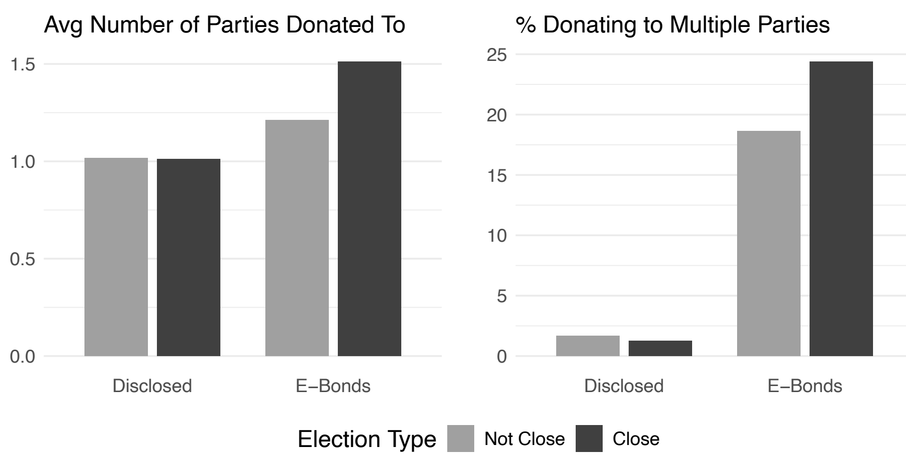
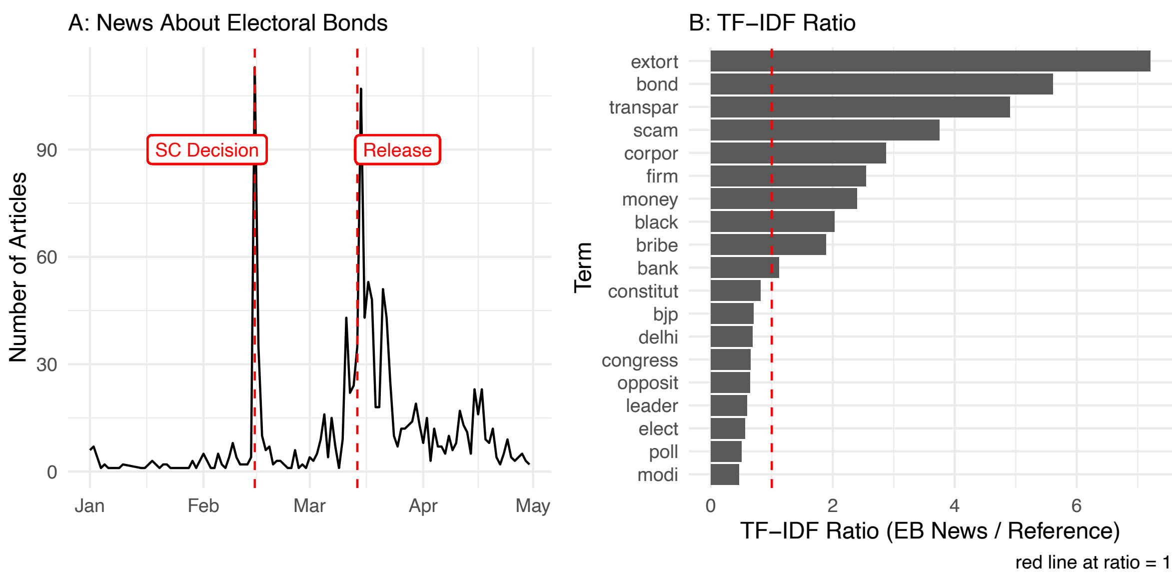


FIGURE A15. News Coverage About Electoral Bonds



Note: A: Count of news articles mentioning electoral bonds, from `newsapi.org`. B: Reports for specific terms the ratio of TF-IDF between the corpus of news mentioning electoral bonds, and a reference corpus of news about elections and India. A ratio of greater than 1 indicates the term being more prominently mentioned in electoral bonds coverage than in general elections-related news in India.

TABLE A1. Conditional ATT on Cumulative Returns

	Cumulative Abnormal Return			Cumulative Excess Returns		
	(1)	(2)	(3)	(4)	(5)	(6)
Post x Donor	−0.015**	−0.020**	−0.008	−0.014*	−0.018*	−0.005
	(0.005)	(0.007)	(0.007)	(0.006)	(0.007)	(0.008)
CAR Window	[0,1]	[0,7]	[0,10]	[0,1]	[0,7]	[0,10]
Num Stocks	1458	1458	1458	1458	1458	1458
FE: ISIN	✓	✓	✓	✓	✓	✓
FE: Trading Day	✓	✓	✓	✓	✓	✓
R2	0.658	0.653	0.567	0.616	0.644	0.564

Note: OLS estimation based on equation **??**, with period dummies interacted with total assets, leverage, return on equity, market capitalization as of Feb 15, and NIC product section for each firm. Firm financial data as of September 30, 2023. Firm-clustered standard errors reported in parentheses.

TABLE A2. Description of Mechanisms

Mechanism	Category	N	Total Donations (INR bn)	Avg Size (INR bn)
Fundamental Updating	New Donor	40	5.0	206
	Known Donor	48	14.6	450
Fundamental Updating	Low Amount	48	2.0	163
	High Amount	40	17.5	550
Reputational Cost	Small Firm	44	5.2	47
	Large Firm	44	14.4	631
Reputational Cost	Low Media Coverage	55	8.2	143
	High Media Coverage	33	11.4	666
	Control	1449	0	317.0

Note: Size: total assets as of September 30, 2023.

Corporate Dark Money in Politics: Evidence from India
Appendix

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London Business School

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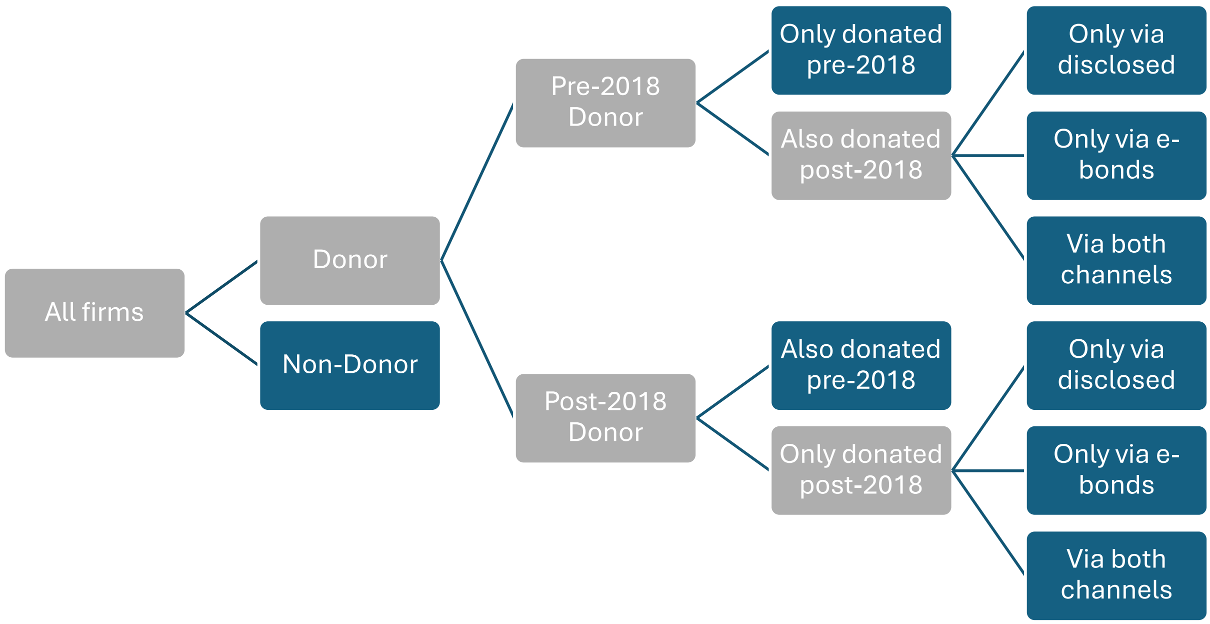
INSEAD

January 15, 2026

Appendix A. Firm Characteristics by Donation Channel

FIGURE A1. Donation Flowchart



Note: Flowchart of donation decision. Cells in blue indicate categories of companies with detailed characteristics presented in tables below.

Here we provide detailed characteristics of donors by each donation channel category.

We split the characteristics into two tables: firms that donated pre-2018, i.e. before the introduction of the electoral bonds channel. And firms that donated after the introduction of the channel. See figure A1 for a visual depiction of the donation choice.

Firm Characteristics by Donor Type

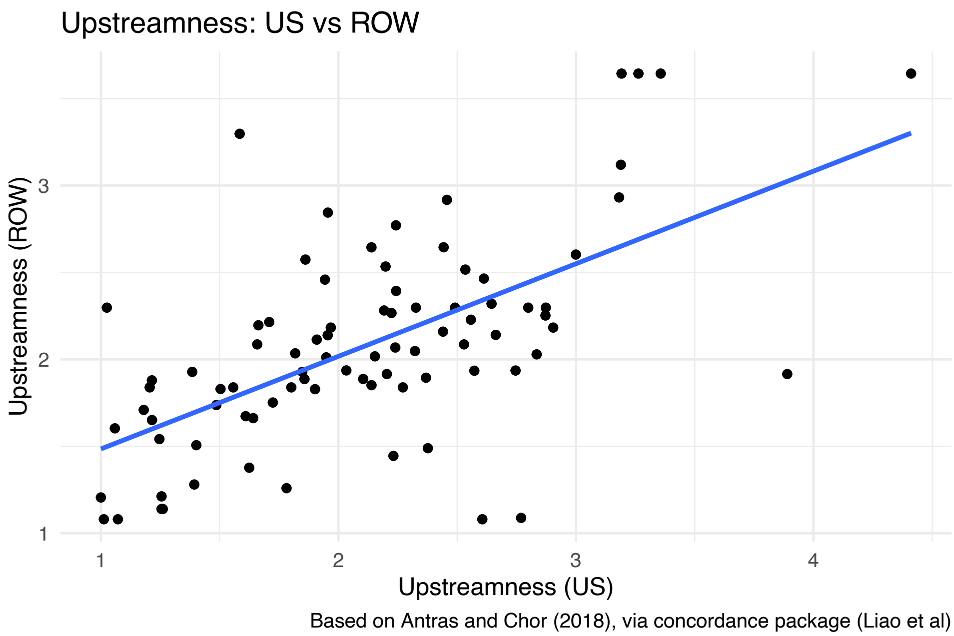
		Pre-2017 Donors			
	Non-Donor	Only Pre	Pre+Post Disclosed Only	Pre+Post Bond Only	Pre+Post Both
No. Firms	1,183,733	2,656	437	38	62
Avg Age (yrs)	14	26	28	33	40
Avg Paid-up Capital (INR, m)	34	813	473	626	1,330
Share Public	0.005	0.085	0.165	0.395	0.371
Industry Share	NA	NA	NA	NA	NA
Manufacturing	0.192	0.307	0.339	0.368	0.419
IT	0.093	0.023	0.023	0.026	0.016
Construction	0.083	0.191	0.247	0.105	0.113
Real Estate	0.057	0.082	0.059	0.053	0.081
Finance	0.043	0.045	0.034	0.158	0.032
Utilities	0.011	0.014	0.007	0.079	NA
Mining	0.009	0.020	0.018	NA	0.016
State Share	NA	NA	NA	NA	NA
Andhra Pradesh	0.029	0.020	0.029	NA	0.029
Delhi	0.144	0.137	0.121	0.154	0.074
Gujarat	0.045	0.170	0.215	0.077	0.088
Haryana	0.025	0.011	0.010	0.026	0.029
Karnataka	0.056	0.029	0.031	NA	0.015
Maharashtra	0.165	0.271	0.196	0.333	0.279
Punjab	0.012	0.013	0.035	NA	0.015
Tamil Nadu	0.101	0.055	0.080	NA	0.044
Telangana	0.046	0.040	0.035	0.077	0.103
Uttar Pradesh	0.112	0.031	0.041	0.051	0.088
West Bengal	0.090	0.059	0.039	0.205	0.088

Firm Characteristics by Donor Type

		Post-2017 Donors			
	Non-Donor	Post+Pre Also	Post-Disclosed Only	EBond Only	Post-Both
No. Firms	1,183,733	537	3,021	563	66
Avg Age (yrs)	14	30	22	23	26
Avg Paid-up Capital (INR, m)	34	583	187	791	942
Share Public	0.005	0.205	0.064	0.107	0.212
Industry Share	NA	NA	NA	NA	NA
Manufacturing	0.192	0.350	0.336	0.249	0.303
IT	0.093	0.022	0.025	0.028	0.045
Construction	0.083	0.222	0.199	0.144	0.106
Real Estate	0.057	0.061	0.066	0.073	0.045
Finance	0.043	0.043	0.023	0.067	0.076
Utilities	0.011	0.011	0.014	0.082	0.015
Mining	0.009	0.017	0.016	0.020	0.076
State Share	NA	NA	NA	NA	NA
Andhra Pradesh	0.029	0.027	0.021	0.028	0.028
Delhi	0.144	0.117	0.170	0.110	0.099
Gujarat	0.045	0.191	0.138	0.041	0.099
Haryana	0.025	0.013	0.028	0.011	0.014
Karnataka	0.056	0.027	0.022	0.038	NA
Maharashtra	0.165	0.215	0.140	0.156	0.183
Punjab	0.012	0.030	0.016	0.003	0.028
Tamil Nadu	0.101	0.070	0.085	0.106	0.042
Telangana	0.046	0.045	0.038	0.145	0.127
Uttar Pradesh	0.112	0.047	0.082	0.038	NA
West Bengal	0.090	0.055	0.039	0.224	0.113

Appendix B. Upstreamness

FIGURE A2. Upstreamness ROW vs Upstreamness USA



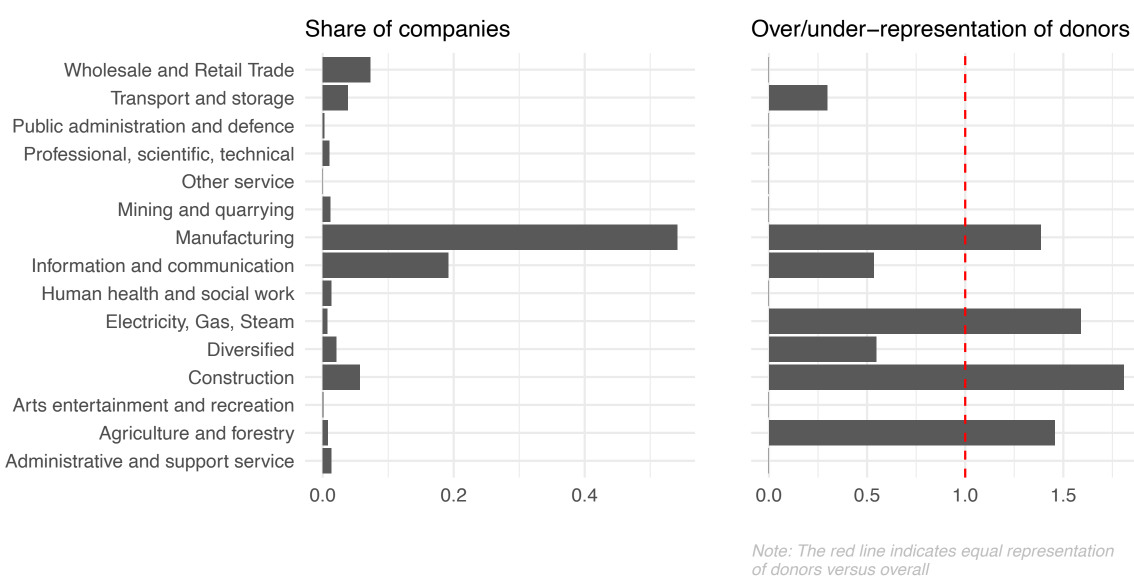
Appendix C. Donor Status Covariates

TABLE A1. Correlations with Donor Status

	(1)	(2)	(3)	(4)	(5)
(Intercept)	−0.195	−0.368	0.052	0.057	−0.331
	(0.031)	(0.049)	(0.009)	(0.006)	(0.054)
log(marketcap)	0.024				0.011
	(0.003)				(0.005)
log(total_assets)		0.025			0.017
		(0.003)			(0.006)
leverage			0.000		0.000
			(0.000)		(0.000)
return_on_equity				0.000	0.000
				(0.000)	(0.000)
Num.Obs.	1537	1537	1537	1537	1537
R2	0.044	0.047	0.000	0.000	0.050

Standard errors in parentheses

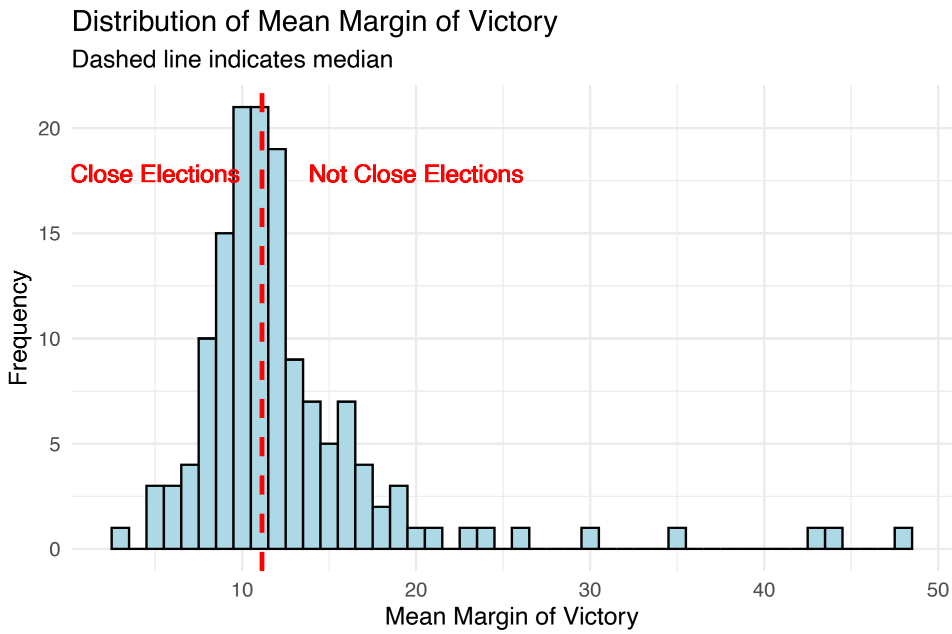
FIGURE A3. Sector distribution



Note: The left panel represents the sectoral distribution of all companies traded on the National Stock Exchange. The right panel shows the sectoral distribution of publicly listed donors relative to the overall sectoral distribution. Manufacturing, utilities (electricity, gas, steam), construction, and agricultural sector companies are overrepresented as donors. Sectors represent NIC "Section" divisions.

Appendix D. Margin of Victory

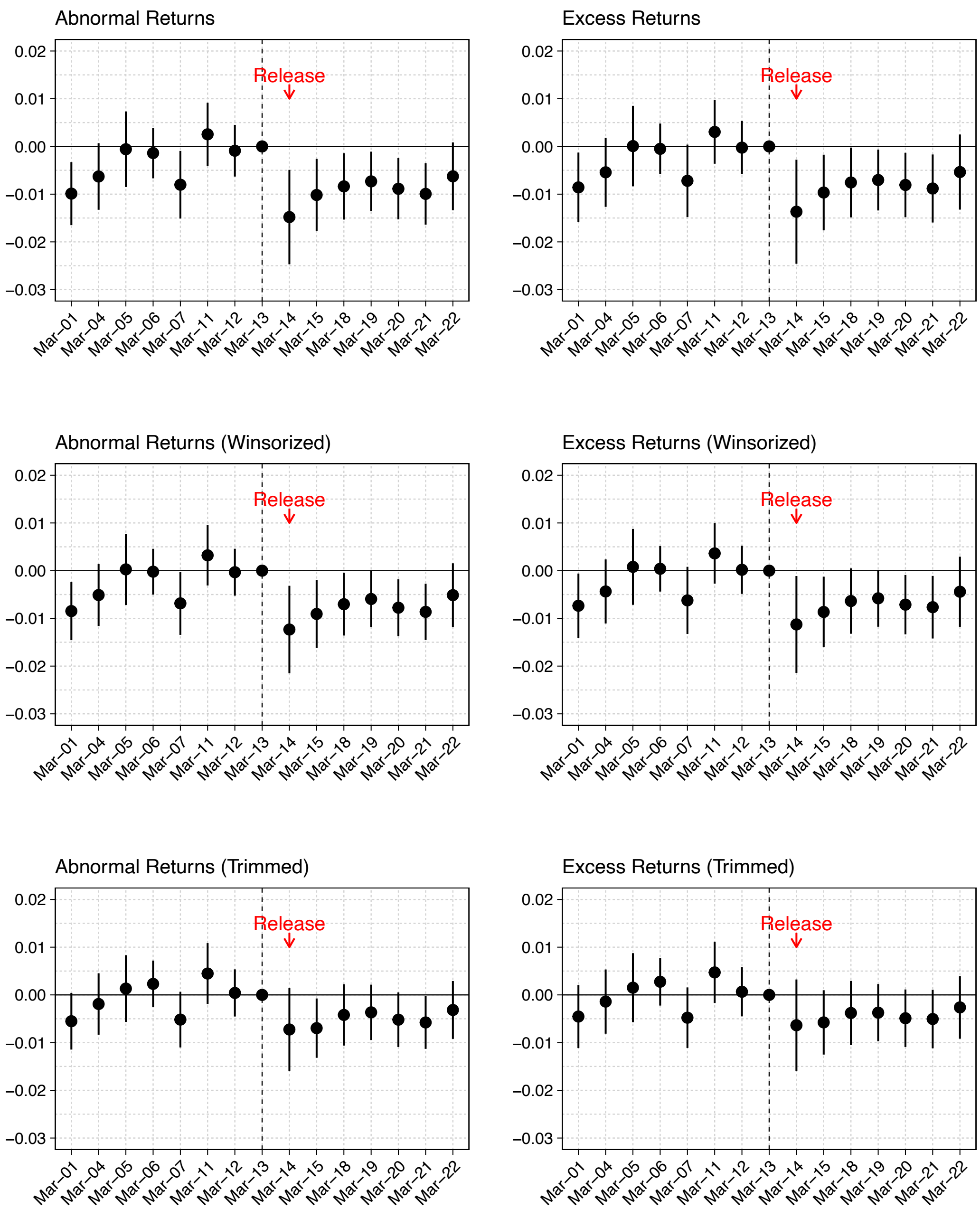
- India has single-member district FPTP elections.
- Margin of Victory: $\text{MOV}_d = \text{VoteShare}_{1st} - \text{VoteShare}_{2nd}$ in district d
- Mean MOV per state-election: $\overline{\text{MOV}}_{s,e} = \frac{1}{N}\sum_d \text{MOV}_d$
- "Close election" defined as $\overline{\text{MOV}}_{s,e}$ below median



Appendix E. Event Study

E.1. Plots

FIGURE A4. Daily Returns Event Study Plots



Note: Winsorizing and trimming daily returns ensures results are not driven by outliers. Winsorized: Daily returns less than the first percentile or greater than the 99th percentile of daily returns capped to the 1st or 99th percentile. Trimmed: Daily returns restricted to 1-99th percentile of daily returns.

E.2. Tables

TABLE A2. Daily Return Event Study

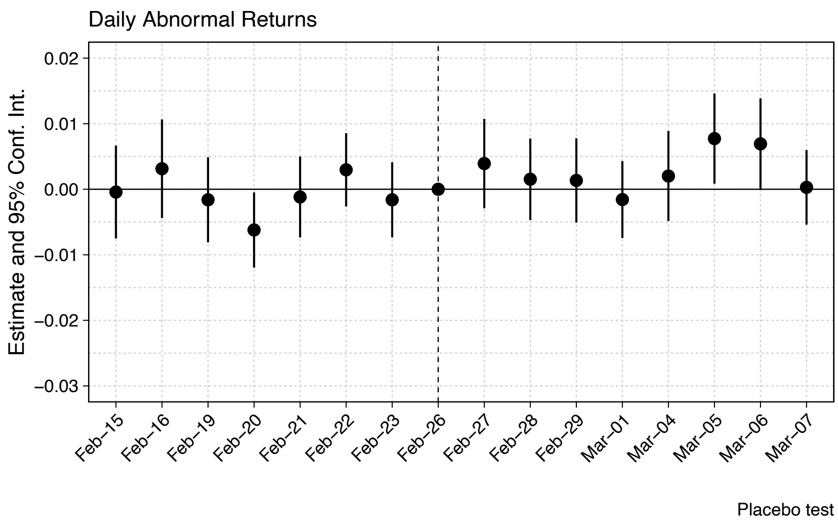
	Abnormal Return			Excess Returns		
	(1)	(2)	(3)	(4)	(5)	(6)
Mar-01 × is_donor	−0.011	−0.009	−0.007	−0.010	−0.009	−0.006
	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Mar-04 × is_donor	−0.005	−0.004	−0.001	−0.004	−0.003	0.000
	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Mar-05 × is_donor	−0.005	−0.004	−0.002	−0.005	−0.004	−0.002
	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
Mar-06 × is_donor	−0.001	0.000	0.002	−0.001	0.000	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Mar-07 × is_donor	−0.009	−0.008	−0.006	−0.009	−0.008	−0.006
	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)
Mar-11 × is_donor	0.002	0.003	0.004	0.003	0.003	0.004
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Mar-12 × is_donor	0.001	0.001	0.001	0.001	0.001	0.002
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Mar-14 × is_donor	−0.015	−0.013	−0.009	−0.014	−0.013	−0.009
	(0.005)	(0.005)	(0.004)	(0.006)	(0.005)	(0.005)
Mar-15 × is_donor	−0.010	−0.009	−0.007	−0.010	−0.009	−0.006
	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)
Mar-18 × is_donor	−0.007	−0.006	−0.003	−0.007	−0.006	−0.003
	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Mar-19 × is_donor	−0.007	−0.006	−0.004	−0.007	−0.006	−0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Mar-20 × is_donor	−0.008	−0.007	−0.005	−0.008	−0.007	−0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Mar-21 × is_donor	−0.010	−0.009	−0.006	−0.010	−0.008	−0.005
	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)
Mar-22 × is_donor	−0.007	−0.006	−0.005	−0.006	−0.005	−0.005
	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)
Modification		Winsorized	Trimmed		Winsorized	Trimmed
Num.Obs.	23 055	23 055	22 440	23 055	23 055	22 447
R2	0.317	0.339	0.331	0.301	0.321	0.311
Std.Errors	by: isin	by: isin	by: isin	by: isin	by: isin	by: isin
FE: ISIN	✓	✓	✓	✓	✓	✓
FE: Trading Day	✓	✓	✓	✓	✓	✓

Note: OLS estimation based on equation **??**, with period dummies interacted with total assets, leverage, return on equity, market cap, and NIC product section for each firm. Firm financial data as of September 30, 2023. Market cap is as of Feb 15, 2024. Firm-clustered standard errors reported in parentheses.

E.3. Placebo Test

Replace event date with a placebo date from two weeks before the information shock. I choose Feb 26 as the reference date. Figure A5 shows no systematic pattern of difference in abnormal returns between firms revealed on the list of donors and not.

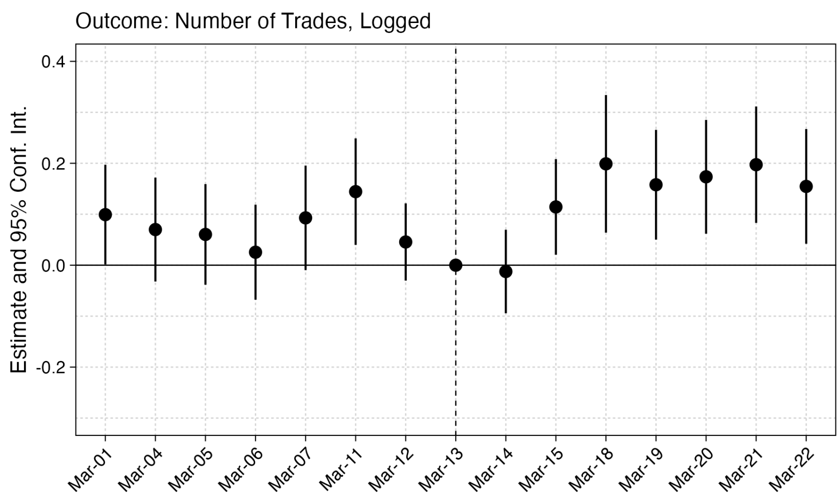
FIGURE A5. Event Study Placebo Test



Note: 95% confidence interval. Size, leverage, profits, market capitalization (as of Feb 15, 2024) and industry sections all interacted with time dummies.

E.4. Trading Volumes

FIGURE A6. Number of Trades



Note: 95% confidence interval. Size, leverage, profits, market capitalization (as of Feb 15, 2024) and industry sections all interacted with time dummies.

Appendix F. Cumulative Abnormal Returns

F.1. CATT on Cumulative Abnormal Returns

TABLE A3. CATT on Cumulative Abnormal Returns

	1	2	3	4	5	6	7	8	9	10
Post x Donor	−0.015	−0.017	−0.016	−0.015	−0.015	−0.017	−0.015	−0.006	−0.005	−0.004
	(0.005)	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
R2	0.652	0.653	0.649	0.644	0.625	0.643	0.649	0.618	0.591	0.565
Trading days	1	2	3	4	5	6	7	8	9	10
Num Stocks	1537	1537	1537	1537	1537	1537	1537	1537	1537	1537

Firm-clustered standard errors in parentheses

Appendix G. Synthetic Control Method

I follow Acemoglu et al. (2016), given its similar setting of multiple treated units, and aggregate treated firms' actual returns deviations from their synthetic counterfactuals. I estimate confidence intervals using permutation tests as recommended by Abadie et al. (2010); Abadie (2021).

The principle behind this approach is to construct a synthetic match for each treated unit by weighting "donor" (i.e. control) units such that pre-event trends are similar. After constructing such a match, the effect of the event is simply the deviation in behavior between the actual treated unit and its synthetic pair. This calculates a treatment effect for each treated unit individually. I calculate control unit weights over an estimation period of one year, ending one month before the event date.

Formally, I construct a synthetic match for each treated firm i given each control firm j by solving the following optimization problem:

$$\begin{aligned} &\arg\min_{w_j^i} \sum_{t \in \text{Estimation window}} \left[R_{it} - \sum_j w_j^i R_{jt} \right]^2 \\ &\text{s.t.} \quad \sum_j w_j^i = 1 \quad \text{and} \quad w_j^i \geq 0 \end{aligned} \tag{A1}$$

where R_{it} is the daily return for treated company i on date t during the estimation window. w_j^i is the weight of control unit j that is calculated in this optimization problem. $\sum_j w_j^i = 1$ and $w_j^i \geq 0$ ensure non-negative weights that sum to 1.

After optimal weights are calculated, I calculate synthetic returns for each treated unit i with the following equation:

$$\hat{R_{it}} = \sum_j w_j^i R_{jt}$$

And Abnormal Returns is simply the difference between actual returns and synthetic returns:

$$AR_{it} = R_{it} - \hat{R_{it}}$$

Estimating the effect of the event requires defining the event window: τ_1, τ_2. Note, aggregating across multiple treated units to calculate an average effect does not change the individual estimation procedures (Abadie 2021). The effect of revealing treated companies names is estimated as:

$$\hat{\Phi}(\tau_1, \tau_2) = \frac{\sum_{i \in \text{Treatment group}} \frac{\sum_{\tau_1}^{\tau_2} AR_{it}}{\sigma_i}}{\sum_{i \in \text{Treatment group}} \frac{1}{\sigma_i}}, \tag{A2}$$

where $\frac{1}{\sigma_i}$ is a goodness of fit that overweights better matches (similar in spirit to corrections recommended by Ben-Michael et al. (2021)). $\hat{\sigma}_i$ is defined as:

$$\hat{\sigma}_i = \sqrt{\frac{\sum_{t \in \text{Estimation window}} \left(R_{it} - \hat{R}_{it}\right)^2}{T}} \tag{A3}$$

where T is the length of the estimation window (for me, 250 days).

Finally, I take a permutation approach to calculating confidence intervals as recommended by Abadie et al. (2010) which involves calculating a test statistic and comparing how extreme this test statistic is compared to a distribution, and is followed by Acemoglu et al. (2016). I randomly draw 5000 placebo treatment groups from the set of control units. Each group is the same size as the actual treatment group (88 units). For each placebo group, I calculate a treatment effect over several days starting from the event date of March 14, 2024, $\hat{\phi}(\tau_1, \tau_2)$, and construct a distribution of placebo group effects. I compare the real treatment effect to this distribution. Since the hypothesized effect is negative, I conduct a one-sided hypothesis test where I evaluate if the real treatment effect is significant at 5% if it is below the 5th percentile of the placebo group distribution.

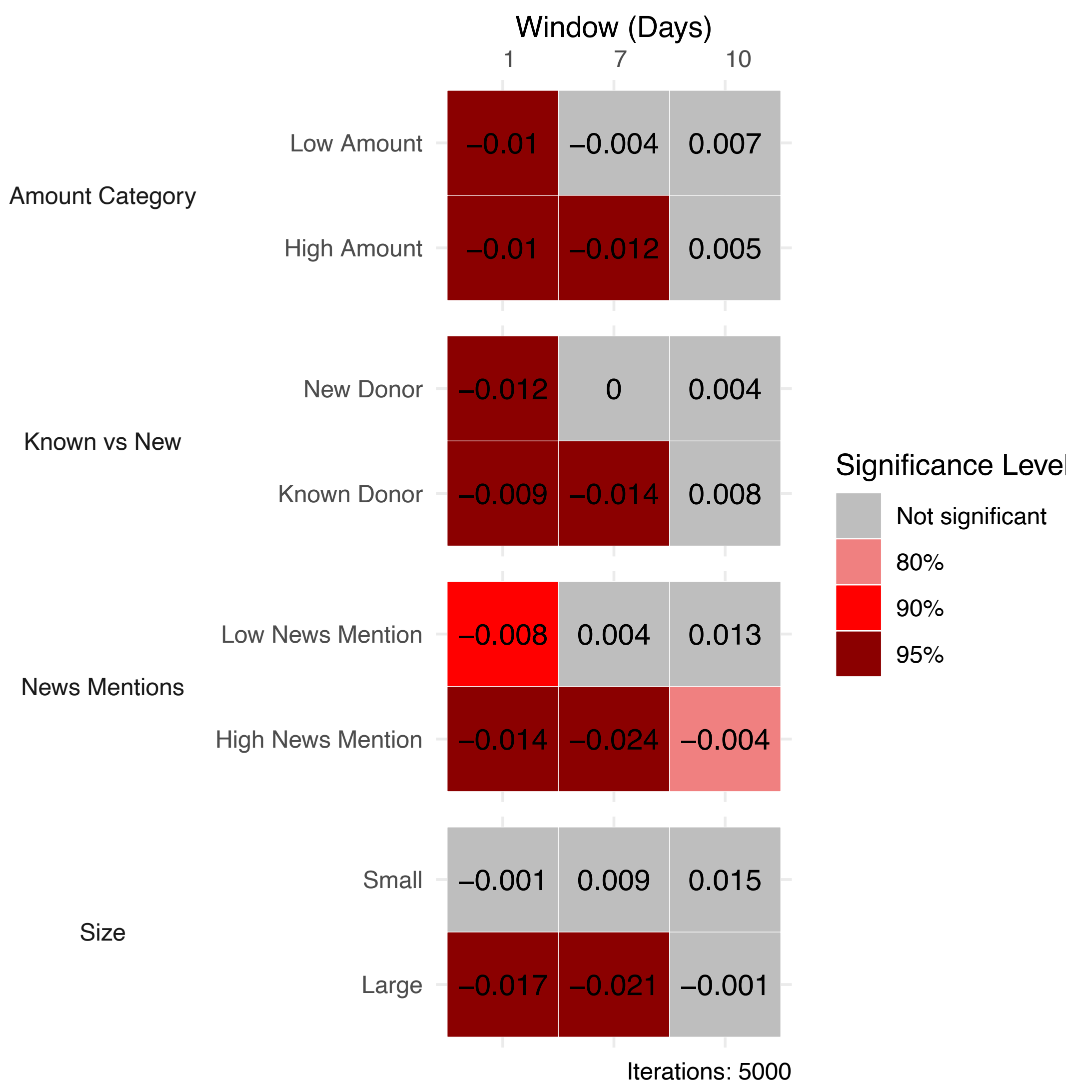
G.1. Results

I take a randomization inference approach to hypothesis testing heterogenous treatment effects. I split the treatment group into treatment arms, and for each treatment arm, I calculate a test statistic of its real treatment effect, and construct a distribution of treatment effects by drawing 5000 placebo treatment groups from the pool of control units, each of the same size as the treatment group. I carry out a one-sided hypothesis test where the treatment effect is significant at X% if it is below $1 - X$% of the distribution. I repeat this procedure for 1 day, 7 days, and 10 days after event onset.

Figure A10 presents the results. Treated units with high news coverage and larger companies tended to see a deeper and more significant abnormal sell-off up to 7 days after the event. Overall effects are largely insignificant 10 days after the event.

The results are broadly similar to the difference-in-difference event study, but an exception is in the "High Amount" treatment arm, which suggests some evidence for a fundamental updating channel. However, ultimately the fact that these heterogenous effects only last a short while suggests a more behavioral reaction than investors re-rating a company's fundamentals.

FIGURE A7. ATT on CAR by Treatment Arms: Synthetic Control Method



Note: Effect size printed inside each grid

Appendix H. Mechanism

H.1. News Mentions

I use newsapi.org, which provides a REST (representational state transfer) API to query current and historical news records from over 150,000 news sources from around the world in multiple languages. Each query returns the headline, a snippet, and a description of each article, along with authorship information, source, and language.

I carry out three sets of searches. First, I construct the *electoral bonds news corpus* by searching for the term “electoral bonds” between Jan 1, 2024 and April 30, 2024. This search produces around 1,200 search results all related to India’s electoral bonds. Panel A in figure **??** shows how articles that meet this search term spike around key dates: the supreme court decision as well as the release date.

Second, I construct a *reference news corpus* by searching for news articles that contain the terms “elections” and “India” between Jan 1, 2024 and April 30, 2024. I include “India” to restrict the geography to India, as `newsapi.org` does not allow geographic filters in setting search parameters.

Finally, for each treated company revealed to be a donor, I search for news that contains the name of the firm and “electoral bonds”, and filter for the period from March 14-28, 2024.

H.1.1. News Text Analysis

I compare the *electoral bonds news corpus* to the *reference news* corpus by computing the term frequency-inverse document frequency (TF-IDF) for key terms in each corpus, and calculating a ratio between each corpus’s TF-IDFs.

$TF-IDF_{ij}$ for each term i in corpus j is defined as the product of Term Frequency (TF_{ij}) and Inverse Document Frequency (IDF_{ij}). TF_{ij} is the count of occurrences of i in corpus j. IDF_{ij} is the log of one over the share of documents in corpus j that contain the term i.

Per Gentzkow et al. (2019), TF-IDF filters out both very rare and very common terms because TF_{ij} will be low for extremely rare terms, and IDF_{ij} will be low for extremely common terms that are present in all documents.

The TF-IDF ratio is defined for each term as:

$$\text{Ratio}_i = \frac{\text{TF-IDF}_{i,j=\text{Electoral Bond News}}}{\text{TF-IDF}_{i,j=\text{Reference News}}} \tag{A4}$$

Table A4 presents the statistics.

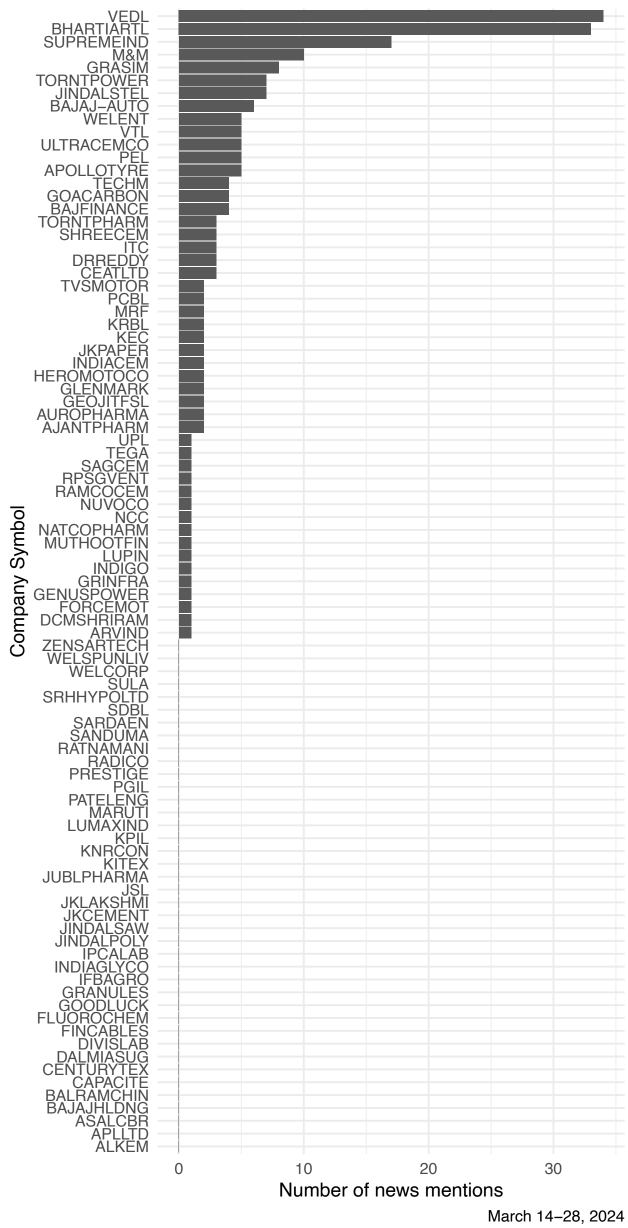
TABLE A4. TF-IDF Comparison

Term	EB News TF-IDF	Reference News TF-IDF	Ratio
extort	61.05	8.47	7.21
bond	325.32	58.00	5.61
transpar	108.47	22.10	4.91
scam	82.94	22.10	3.75
corpor	81.57	28.43	2.87
firm	81.20	31.87	2.55
money	129.58	54.00	2.40
black	58.26	28.78	2.02
bribe	12.46	6.60	1.89
bank	179.57	160.09	1.12
constitut	72.57	88.98	0.82
bjp	299.25	425.54	0.70
delhi	143.57	208.94	0.69
congress	267.01	409.84	0.65
opposit	120.17	187.31	0.64
leader	144.03	240.75	0.60
elect	252.90	451.05	0.56
poll	182.13	359.39	0.51
modi	198.07	429.46	0.46

H.1.2. News coverage for each company

For each donor company, I count the number of articles that contain the name of the company and “electoral bonds” between March 14-28, 2024.

FIGURE A8. Count of news stories about each donor company and electoral bonds



Note: Information from `NewsAPI`. Count of how many news articles were written that contained both the name of the company and included a discussion of electoral bonds between March 14-28, 2024. Source: `NewsAPI.org`

H.2. Heterogeneous Effects

H.2.1. Cumulative Abnormal Returns over 7 Days: Table

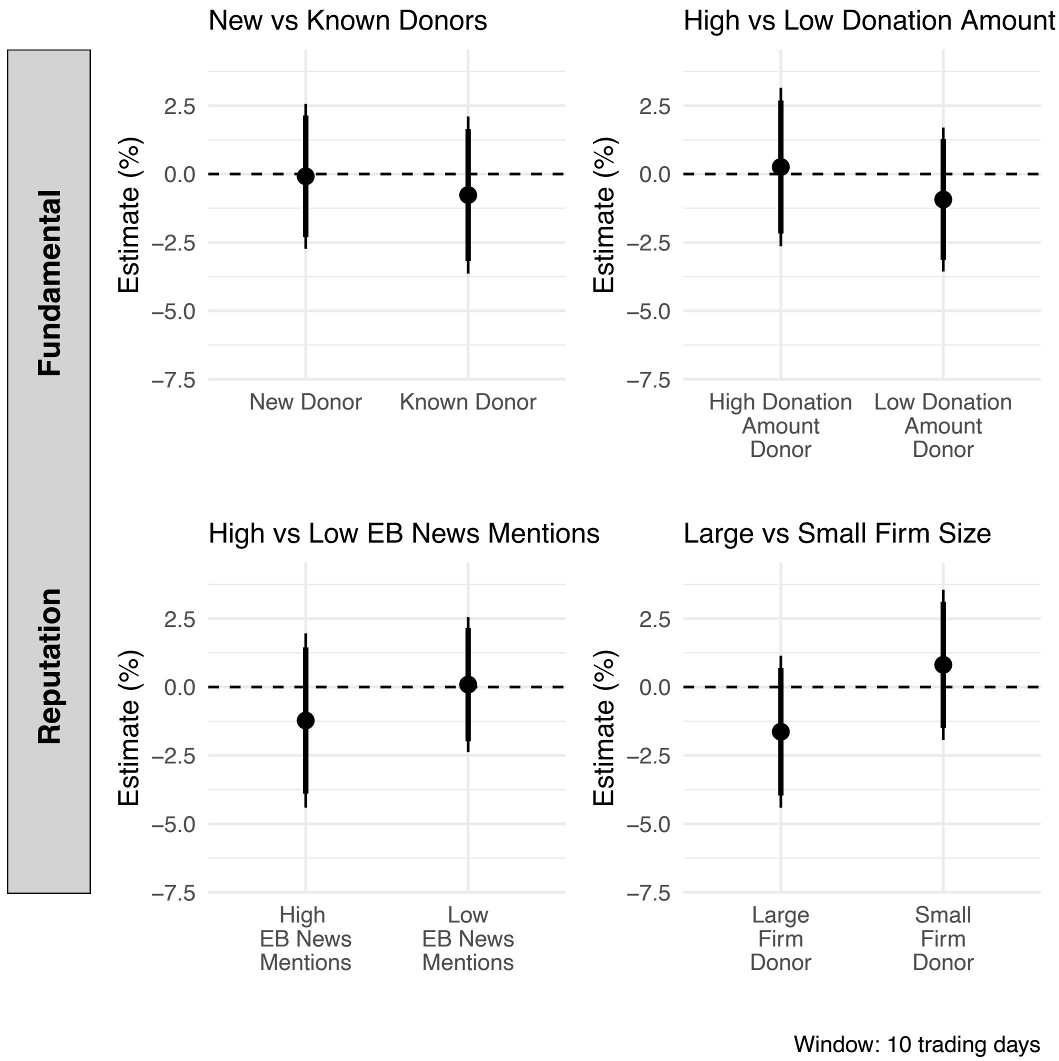
TABLE A5. Heterogenous effect on 7 Day CAR

	New Donor	Amount Donated	Size of Firm	Media Coverage
post × New Donor	−0.013			
	(0.010)			
post × Known Donor	−0.017			
	(0.010)			
post × Amt Donated: Low		−0.015		
		(0.011)		
post × Amt Donated: High		−0.015		
		(0.010)		
post × Firm Size: Small			0.004	
			(0.010)	
post × Firm Size: Large			−0.034	
			(0.010)	
post × News Mentions: Low				−0.004
				(0.009)
post × News Mentions: High				−0.034
				(0.011)
R2	0.649	0.649	0.650	0.650
Num.Obs.	3074	3074	3074	3074

Cumulative abnormal returns over 7 trading days; firm-clustered standard errors in parentheses.

H.2.2. Cumulative Abnormal Returns over 10 Days

FIGURE A9. Conditional ATT: Cumulative Abnormal Returns by Treatment Arm



Note: For 10 days after the event date. Overall effects are negligible, as are heterogeneity across treatment arms.

H.3. Synthetic Control Method

I take a randomization inference approach to hypothesis testing heterogenous treatment effects. I split the treatment group into treatment arms, and for each treatment arm, I calculate a test statistic of its real treatment effect, and construct a distribution of treatment effects by drawing 5000 placebo treatment groups from the pool of control units, each of the same size as the treatment group. I carry out a one-sided hypothesis test where the treatment effect is significant at $X\%$ if it is below $1 - X\%$ of the distribution. I repeat this procedure for 1 day, 7 days, and 10 days after event onset.

Figure A10 presents the results. Treated units with high news coverage and larger companies tended to see a deeper and more significant abnormal sell-off up to 7 days after the event. Overall effects are largely insignificant 10 days after the event.

The results are broadly similar to the difference-in-difference event study, but an exception is in the "High Amount" treatment arm, which suggests some evidence for a fundamental updating channel. However, ultimately the fact that these heterogenous effects only last a short while suggests a more behavioral reaction than investors re-rating a company's fundamentals.

FIGURE A10. ATT on CAR by Treatment Arms: Synthetic Control Method

Note: Effect size printed inside each grid

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